2013-06

Effectiveness of Unmanned Aerial Vehicles in helping secure a border characterized by rough terrain and active terrorists

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

EFFECTIVENESS OF UNMANNED AERIAL VEHICLES IN HELPING SECURE A BORDER CHARACTERIZED BY ROUGH TERRAIN AND ACTIVE TERRORISTS

by

Begum Y. Ozcan

June 2013

Thesis Advisor: Thomas W. Lucas
Second Reader: Jeffrey Appleget

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE	*Form Approved OMB No. 0704–0188*

1. AGENCY USE ONLY *(Leave blank)*	**2. REPORT DATE** June 2013	**3. REPORT TYPE AND DATES COVERED** Master's Thesis

4. TITLE AND SUBTITLE
EFFECTIVENESS OF UNMANNED AERIAL VEHICLES IN HELPING SECURE A BORDER CHARACTERIZED BY ROUGH TERRAIN AND ACTIVE TERRORISTS

5. FUNDING NUMBERS

6. AUTHOR(S) Begum Y. Ozcan

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Naval Postgraduate School
Monterey, CA 93943–5000

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES)
N/A

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB Protocol number ____N/A____.

12a. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited

12b. DISTRIBUTION CODE

13. ABSTRACT

Border security is of great importance to most countries. Turkey has been in conflict with terrorist groups since the 1980s. Up to now, more than 40,000 people have been killed, including Turkish soldiers and civilians. The porosity and openness of Turkey's Iraq border, combined with the rugged topography of the region, creates a passage for terrorist groups to move materiel and personnel. Technical capabilities of Unmanned Aerial Vehicles UAVs can be used to improve coverage along borders. However, their effectiveness is highly dependent on the characteristics of the region. In this study, 87 km of the Turkey-Iraq border is modeled in Map Aware Non Uniform Automata (MANA) to examine the potential impact of UAVs on detecting and classifying terrorists seeking passage from Northern Iraq into Turkey. The results from the 103,200 simulated terrorist incursions are analyzed using descriptive statistics, stepwise linear regression, lasso regression, regression trees, and random forests. The use of UAVs is found to be efficient in the detection and classification of terrorists in this region. The analysis techniques reveal that the most significant factors are the UAV's detection and classification performance, as well as the terrorists' counter detection capabilities. Thus, Turkey (and countries trying to secure similar terrain) should purchase (or build) and employ hard-to-detect UAVs with sophisticated sensors.

14. SUBJECT TERMS Border security, Unmanned Aerial Vehicle, Intelligence Surveillance and Reconnaissance, Simulation, Agent- Based Modeling, Design of Experiments

15. NUMBER OF PAGES 117

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	**18. SECURITY CLASSIFICATION OF THIS PAGE**	**19. SECURITY CLASSIFICATION OF ABSTRACT**	**20. LIMITATION OF ABSTRACT**
Unclassified	Unclassified	Unclassified	UU

NSN 7540–01–280–5500 Standard Form 298 (Rev. 2–89)
Prescribed by ANSI Std. 239–18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release; distribution is unlimited

EFFECTIVENESS OF UNMANNED AERIAL VEHICLES IN HELPING SECURE A BORDER CHARACTERIZED BY ROUGH TERRAIN AND ACTIVE TERRORISTS

Begum Y. Ozcan
First Lieutenant, Turkish Air Force
B.S., Turkish Air Force Academy, 2007

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
June 2013

Author: Begum Y. Ozcan

Approved by: Thomas W. Lucas
Thesis Advisor

Jeffrey Appleget
Second Reader

Robert F. Dell
Chair, Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

Border security is of great importance to most countries. Turkey has been in conflict with terrorist groups since the 1980s. Up to now, more than 40,000 people have been killed, including Turkish soldiers and civilians. The porosity and openness of Turkey's Iraq border, combined with the rugged topography of the region, creates a passage for terrorist groups to move materiel and personnel. Technical capabilities of Unmanned Aerial Vehicles UAVs can be used to improve coverage along borders. However, their effectiveness is highly dependent on the characteristics of the region. In this study, 87 km of the Turkey-Iraq border is modeled in Map Aware Non Uniform Automata (MANA) to examine the potential impact of UAVs on detecting and classifying terrorists seeking passage from Northern Iraq into Turkey. The results from the 103,200 simulated terrorist incursions are analyzed using descriptive statistics, stepwise linear regression, lasso regression, regression trees, and random forests. The use of UAVs is found to be efficient in the detection and classification of terrorists in this region. The analysis techniques reveal that the most significant factors are the UAV's detection and classification performance, as well as the terrorists' counter detection capabilities. Thus, Turkey (and countries trying to secure similar terrain) should purchase (or build) and employ hard-to-detect UAVs with sophisticated sensors.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS AND ABBREVIATIONS

ABMS	Agent-Based Modeling and Simulation
AOR	Area of Responsibility
BMP	Bitmap
CAB	Combined Arms Battalion
CBRN	Chemical, Biological, Radiological, and Nuclear
DEM	Digital Elevation Model
DoD	Department of Defense
DOE	Design of Experiment
DPs	Design Points
DTA	Defense Technology Agency
E-O	Electro-Optical
EW	Electronic Warfare
GUI	Graphical User Interface
ISR	Intelligence, Surveillance, and Reconnaissance
LASSO	Least Absolute Shrinkage and Selection Operator
LH	Latin Hypercube
LOS	Line-of-Sight
MANA	Map Aware Non-Uniform Automata
MANA-V	Map Aware Non-Uniform Automata-Vector
MEB	Marine Expeditionary Brigade
MOE	Measure of Effectiveness
MPR	Maritime Patrol Review
MSE	Mean Square Error
NCW	Network Centric Warfare
NOLH	Nearly Orthogonal Latin Hypercube
NZDF	New Zealand Defense Force
OR	Operations Research
PKK	Kurdish Workers' Party
RGB	Red, Green, and Blue
RNZAF	Royal New Zealand Air Force

ROK	Republic of Korea
SA	Situational Awareness
SE	Southeast
SEED	Simulation Experiments and Effectiveness Design
SIGINT	Signals Intelligence
UAS	Unmanned Air System
UAV	Unmanned Aerial Vehicle

THESIS DISCLAIMER

The reader is cautioned that the computer programs presented in this research may not have been exercised for all cases of interest. While every effort has been made, within the time available, to ensure that the programs are free of computational and logical errors, they cannot be considered validated. Any application of these programs without additional verification is at the risk of the user.

THIS PAGE INTENTIONALLY LEFT BLANK

EXECUTIVE SUMMARY

Border security is of great importance to most countries. Many countries spend a significant portion of their budget protecting their border against terrorists, smugglers, and illegal immigrants. Illegal activities cause direct effects, especially for the regions adjacent to borders, and indirect effects for the entire country. Turkey has been in conflict with terrorist groups since the 1980s. Up to now, more than 40,000 people have been killed, including Turkish soldiers and civilians. Terrorist activities have also ruined the socioeconomic and social stability of the region.

The preeminent terrorist threat coming from Turkey's borders is the Kurdish Workers Party (PKK). The PKK is an armed Kurdish organization struggling with Turkey. The organization is also listed as a foreign terrorist organization by the U.S Department of Defense (DoD). The southeast (SE) border of Turkey contains the majority of terrorist activities. The region is known for its steep mountains and deep dales. Thus, the soldiers protecting the border have limited lines-of-sight (LOS). These conditions reduce the probability of detecting PKK militants operating or transiting in the region.

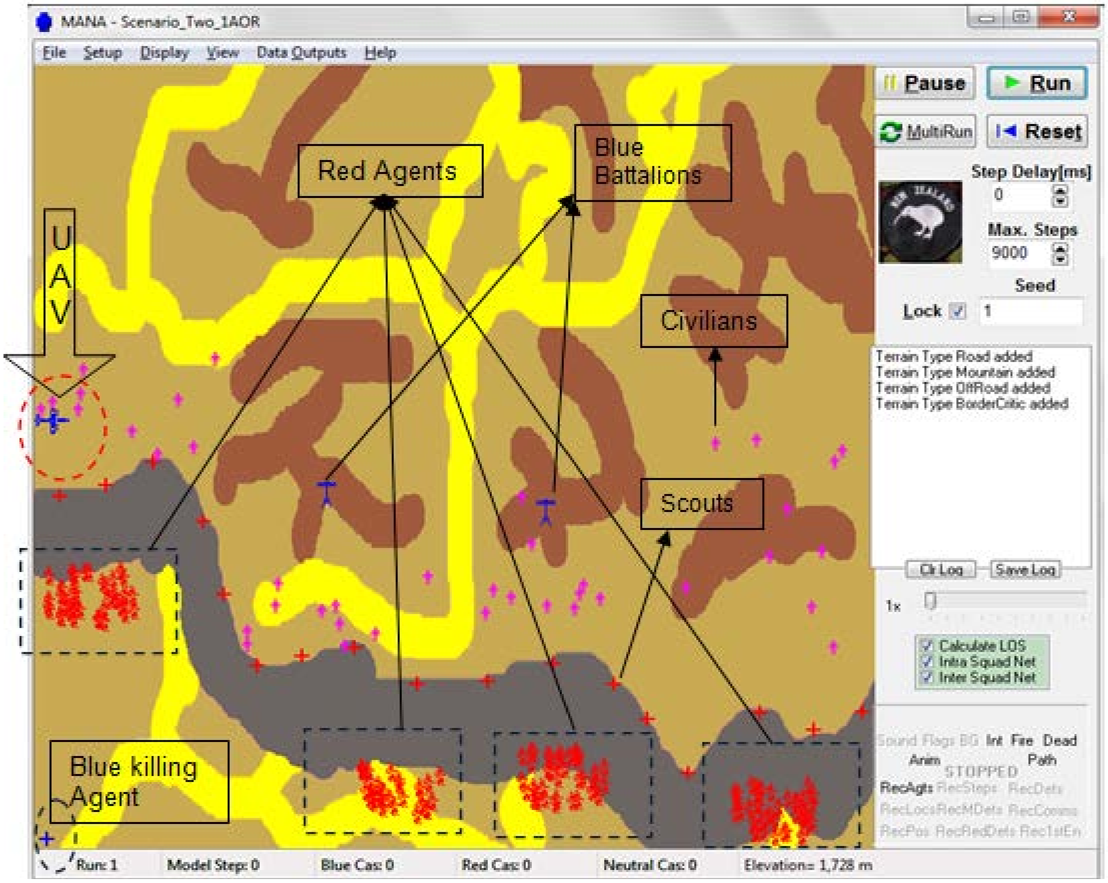
The PKK terrorist organization also takes advantage of the gaps along the border in its illegal drug trafficking, which supports the organization financially. Terrorists use ever changing guerilla tactics. They cross over the border to attack military outposts and to bring explosives for use in bomb attacks in urban areas. Simultaneous raids are a recently used tactic of the terrorist organization. In addition to military stations, the terrorists attack military and police lodgings, prefectures, and government agencies.

In Turkey, conventional Turkish military and police forces play a key role in both the interdiction of illegal drugs and in defending the country against terrorist attacks. The porosity and openness of Turkey's Iraq border have been a problem in counterterrorism. The Qandil Mountains, which are located south of the

Turkey-Iraq border, provide an operations center as well as tactical and practical advantages for the terrorists. Combined with the rugged topography of the region, border porosity creates a passage for terrorist groups to move material and personnel. The terrain also makes it difficult for military outposts to support each other. In order to decrease illegal activities, including terrorism, effective border monitoring is essential. Detection of terrorist threats is vital for the safety of the border region, assets along the borders, and security of the whole country.

Unmanned Aerial Vehicles (UAVs), aerial vehicles that can be piloted remotely, are a critical component of modern day intelligence, reconnaissance, and surveillance (ISR). Technical capabilities of UAVs can be used to improve coverage along borders. Advanced Electro-Optical (E-O) identification technology, UAV loiter capability, the range of UAVs compared to other patrol assets, and their low price explains why UAVs should play a key role in ISR missions. The growing demand for UAVs is also based on avoiding military casualties. In terms of today's casualty averse military environment, the consequences of losing an airman and a UAV cannot be compared. UAVs can be designed to fly under extreme conditions that are risky for pilots. They can fly over extreme altitudes for extended periods without suffering the emotional and physical effects experienced by humans. UAVs also improve situational awareness. However, their effectiveness is highly dependent on the characteristics of the region in which they are deployed. This thesis examines the effectiveness of UAVs in helping secure a border characterized by rough terrain and active terrorists.

The baseline incursion scenario analyzed in this research was developed, based on a skirmish between a guerilla team and a battalion in the Southeast region of Turkey, using Map Aware Non Uniform Automata (MANA). For this thesis, 87 km of the Turkey-Iraq border was chosen as the area of interest to model five different scenarios including different numbers of UAVs (0 up to 4). The following image provides an overview to the battlefield with the agents for the scenario with one UAV.



Overview of scenario including one UAV.

UAVs are responsible for monitoring the 87 km border, which is divided into Areas of Responsibility (AORs) (from 0 up to 4). Each UAV is capable of detecting, classifying, and tracking illegal entrants. A UAV follows predefined waypoints in the default state. Once it detects an activity, it then proceeds to the detection area for classification. The UAV tracks the classified agent if it is a Red Agent. Otherwise, the UAV keeps following its waypoints. There are two Blue Battalions in the model and the destination of Red Agents is set depending on the location of these battalions. Red Teams represent the terrorists. There are four groups of Red Teams trying to cross the border. Initially, each group is located at four different points along the Iraq part of the border. They follow their waypoints into Turkey and try to avoid the UAVs along their path. There are 17 Scouts distributed along the border to provide information on UAV activities to the Red Teams. Scouts have a stationary observation point. Scouts are able to extend their sensor range by using binoculars. Neutrals are the agents that cause distraction to the UAVs until they are classified as neutral. However, Neutrals can provide information on UAV activities to the Red Agents in some scenarios.

Following the creation of the base model, a Nearly Orthogonal Latin Hypercube (NOLH) design is used to provide maximum information from the experimental design for the 21 factors in this study. The impact of UAVs on detection and classification of terrorists is examined by varying factors in the model: such as the number of UAVs, UAV sensor range, UAV speed, number of terrorists, detection, classification and communication range of terrorist and scouts, etc. In addition to the factors varied in the design, there are also 13 dependent input variables that are set as a function of some factors: UAV classification range, UAV classification probability, time between detections, and UAV fuel usage rate. The resulting experimental design is crossed with the number of UAVs (1 up to 4). Afterwards, each of the 512 design points is replicated 200 times, producing a final data set of 103,200 observations.

Descriptive statistics, stepwise linear regression, lasso regression, regression trees, and random forests are used to analyze 103,200 simulated terrorist incursions. The analysis techniques highlight similar factors as the most important factors, plus with additional insights. The following list summarizes the primary findings of our analysis conducted based on the results of scenarios:

- Agent-based models provide us a modeling platform to create and analyze scenarios in a short time period.
- The data farming process is a powerful technique to study the effects of numerous factors simultaneously.
- The use of UAVs significantly enhances the detection and classification of terrorists operating or transiting in the region.
- The classification range of a UAV has a strong positive affect in the number of classified terrorists. The first split in the regression tree analysis highlights the importance of having a classification range greater than 5 km.

- The sensor range of terrorists to detect UAVs has a negative impact on the number of classified terrorists. Even though UAV altitude is not highlighted as a significant factor, assigning UAVs at higher altitudes can reduce their probability of detection by terrorists.

- The classification probability of a UAV is also important. A 1% increase in classification probability results in more classified terrorists. Additionally, regression tree analysis yields that a maximum range ($\geq$ 5000 meters) classification probability greater than 0.17 provides better results in the classification of terrorists. From a practical sense, classification probability of a camera, which is onboard the UAV, leads to the number of effective looks needed to search an area. So, this is an important factor to take into account in terms of mission plan and organization.

- We cannot talk about an optimal number of UAVs to assign over the area of interest, but regression tree analysis indicates that assigning three or more UAVs results in more classified terrorists with a lower variance.

- The time between detections of entities is another important factor in terms of a UAV's classification capability. A one second increment of time between detections in the default state causes a larger decrease in the number of classified terrorists than a one second increment of time between detections in enemy contact state.

- Refueling time is a bigger determinant of success than the initial fuel level of a UAV. Thus, it is important for ground bases to be able to quickly get the UAVs back up.

- Increasing the UAV's speed in the default state has a negative impact on UAV classification performance. Regression tree analysis shows that UAV speeds higher than 250 km/hr noticeably decreases the number of classified terrorists. Therefore, the speed of flight is critical. If it is too high, UAVs will quickly occupy images of the terrain and will miss the details. On the contrary, if the speed is too low, then there will be less variation in the occupied image, hence less information will be gathered through the scans.

- The existence of communication links between the civilians and terrorists is another significant factor on UAV performance. The existence of civilian communication with terrorists caused a reduction in the number of classified terrorists. Therefore, SIGINT and electronic warfare (EW) capabilities should be considered in addition to UAV performance characteristics.

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGMENTS

First, I would like to express my appreciations to Turkey and Turkish Air Force for providing me the opportunity to have master's degree at Naval Postgraduate School. It was an invaluable experience for me to have such an advanced education.

I would especially like to thank my thesis advisor, Professor Thomas W. Lucas, for helping me improve my thesis with beneficial insights of simulation and modeling. It would be hard to develop this thesis without his guidance and support. I would also like to thank my Second Reader, Professor Jeffrey Appleget, for his helpful advices.

I would like to thank Mary McDonald for her magnificent support in model development, experimental design, model runs, and being available whenever I needed her assistance. It would be impossible to finish this study without her patience and help.

Finally, and most importantly, I thank my husband, Ozer, for his lovely support and understanding since the beginning of our relationship and during my entire study at Naval Postgraduate School. When needed technical support, it is good to have a computer engineer at home. I love you and our unborn daughter, Azra Nisan, very much.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

“The future is in the skies.”

– **Mustafa Kemal Ataturk**

A. BACKGROUND

Border security is of great importance to most countries. Many countries spend a significant portion of their budget protecting their border against terrorists, smugglers, and illegal immigrants. Illegal activities cause direct effects, especially for the regions adjacent to borders, and indirect effects for the entire country. Turkey has been in conflict with terrorist groups since the 1980s. Up to now, more than 40,000 people have been killed, including Turkish soldiers and civilians [1]. Terrorist activities have also ruined the socioeconomic and social stability of the region.

1. Overview of Turkey’s Borders

Turkey is a Eurasian country located in Western Asia and Southeastern Europe. The country has a total of 2,627 kilometers of land boundaries and 7,200 kilometers of coastline. Turkey is bordered by eight countries: Bulgaria, Greece, Syria, Armenia, Azerbaijan, Iran, Georgia, and Iraq [2]. A majority of the terrorist infiltrations take place from Iraq. In Turkey, conventional Turkish military and police forces play a key role in both the interdiction of illegal drugs and in defending the country against terrorist attacks.

The porosity and openness of Turkey’s Iraq border have been a problem in counterterrorism. The Qandil Mountains, which are located south of the Turkey-Iraq border, provide an operations center as well as tactical and practical advantages for the terrorists [3]. Combined with the rugged topography of the region, border porosity creates a passage for terrorist groups to move material and personnel. The terrain also makes it difficult for military outposts to support each other. In order to decrease illegal activities, including terrorism, effective border monitoring is essential.

2. Overview of Terrorist Activities

The preeminent terrorist threat coming from Turkey's borders is the Kurdish Workers Party (PKK). The PKK is an armed Kurdish organization struggling with Turkey. The organization is also listed as a foreign terrorist organization by the U.S. Department of Defense (DoD) [4]. The southeast (SE) border of Turkey contains the majority of terrorist activities. The region is known for its steep mountains and deep dales. Thus, the soldiers protecting the border have limited lines-of-sight (LOS). These conditions reduce the probability of detecting PKK militants operating or transiting in the region.

PKK groups are well adapted to hard conditions and the environment. Most of their plans take advantage of the geography of the region. The bridges are the only connection between some regions and Turkish battalions. This well-known weakness can be used to increase the response time by keeping reinforcement teams away from an attacked Turkish asset.

The PKK terrorist organization also takes advantage of the gaps along the border in its illegal drug trafficking, which supports the organization financially. Terrorists use ever changing guerilla tactics. They cross over the border to attack military outposts and to bring explosives for use in bomb attacks in urban areas. Simultaneous raids are a recently used tactic of the terrorist organization. In addition to military stations, the terrorists attack military and police lodgings, prefectures, and government agencies. News from the world press reflects how terrorist attacks pose a severe threat to the safety of the Turkish people:

> PKK rebels launched a series of attacks against security forces and village guardsmen within three Turkish provinces; Şırnak, Siirt, Antakya. [5]

> PKK militants clashed with Turkish soldiers near the town of Cukurca, within the Hakkari Province, in the south-east of the country. [6]

> A bomb explosion occurred next to a military bus carrying Turkish soldiers and their relatives in Turkey's largest city of Istanbul. PKK militants are being suspected for carrying out this latest attack. [7]
>
> Around 100 suspected PKK fighters simultaneously attacked four government and security buildings in the small town of Beytüşşebap, near the border with Syria. At least 10 soldiers and 3 attackers were killed during the assault, while 7 soldiers were injured. [8]
>
> A roadside bombing in Turkey's southeastern Bingol Province killed 8 soldiers and injured 9 others, less than a day after 4 officers were killed in an attack near the borders with Iran and Iraq. [9] [10]
>
> An explosive device hidden in a car exploded as an Army patrol was passing by in the eastern Turkish city of Tunceli, killing 6 soldiers and a civilian. Several others were injured in the blast, which authorities blamed on the PKK. [11]
>
> A group of suspected PKK fighters attacked a Turkish Army convoy with rocket-propelled grenades and small arms fire in the country's southeast. At least one bus was completely destroyed, killing 10 soldiers and leaving more than 60 others injured. Witnesses later reported seeing military F-16 jets taking off from the air base in Diyarbakir. [12]

Detection of terrorist threats is essential for the safety of borders, assets along the borders, and security of the whole country. The goal is to completely prevent terrorist groups from accessing Turkey through the border. Once this step is taken, the majority of the terrorists' resources will be confined.

B. RESEARCH QUESTIONS

This research is guided by the following questions:

1. Can Unmanned Aerial Vehicles (UAVs) help detect and classify terrorists over a region characterized by rough topographical conditions and active terrorists?

2. Can UAVs provide early warnings of terrorist attacks, and how many terrorists can be detected?

3. What number of UAVs and performance characteristics best contribute to border security?

4. How do changes in our scenario affect the ability of the UAVs to provide early warning?

C. SCOPE OF THE THESIS

UAVs, aerial vehicles that can be piloted remotely, are a critical component of modern day reconnaissance and surveillance. UAVs came onto the stage in the 1990s. UAVs successfully addressed the deficiency of manned ISR assets in the Gulf War by providing enhanced intelligence, surveillance, and reconnaissance (ISR) capabilities [13], [14]. Additionally, the DoD Report on Desert STORM points out that “UAVs proved excellent at providing an immediately responsive intelligence collection capability” [13], [15]. Technical capabilities of UAVs can be used to improve coverage along borders. Advanced Electro-Optical (E-O) identification technology, UAV loiter capability, the range of UAVs compared to other patrol assets, and their low price explains why UAVs should play a key role in ISR missions. The growing demand for UAVs is also based on avoiding military casualties. In terms of today’s casualty averse military environment, the consequences of losing an airman and a UAV cannot be compared. Manned systems and UAVs can accomplish many of the same tasks. But “UAVs have gained favor as a way to reduce risk to combat troops, the cost of hardware, and the reaction time in a surgical strike” [16], [17] and “to conduct missions in areas that are difficult to access or otherwise considered too high-risk for manned aircraft or personnel on the ground” [16], [18].

UAVs can be designed to fly under extreme conditions that are risky for pilots. They can fly over extreme altitudes for extended periods without suffering the emotional and physical effects experienced by humans. UAVs also improve situational awareness. Hence, the reason unmanned air systems (UAS) appeal to the military is explained in Department of Defense Appropriations Bill of Fiscal Year 2003 as follows:

> In today’s military, unmanned systems are highly desired by combatant commanders for their versatility and persistence. By performing tasks such as surveillance; signals intelligence (SIGINT); precision target designation; mine detection; and

> chemical, biological, radiological, nuclear (CBRN) reconnaissance, unmanned systems have made key contributions to the Global War on Terror. [19]

However, their effectiveness is highly dependent on the characteristics of the region in which they are deployed. This thesis examines the effectiveness of UAVs in helping secure a border characterized by rough terrain and active terrorists. For this purpose, 87 kilometers of Turkey's border with Iraq is modeled in MANA (Map Aware Non-Uniform Automata). The impact of UAVs on detection and classification of terrorists who use the southeast border, characterized by rough terrain, as passage from Northern Iraq into Turkey is examined by varying the following factors in the model: the number of UAVs, UAV sensor range, UAV speed, number of terrorists, detection, classification, and communication range of terrorists and scouts, etcetera. This analysis explains the relationships between a variety of input factors used in the detection and classification process and performance measures.

The rough topography of the region can be seen in Figure 1 and Figure 2, which depict sections of the southeast part of Turkey. Terrorists have to walk long distances in rough terrain while crossing the border. Due to these challenging conditions, terrorists need plenty of time to reach their destination. This time period can be turned into an advantage with an efficient UAV network over the region to enhance situational awareness and real-time imagery. UAVs can detect terrorists before they attack Turkish assets. They can even interrupt the logistic and personnel support chain of terrorists. The priceless benefit of using UAVs can be a significant decrease in losses from terrorist attacks.

Figure 1. Topographic Map of Northern Iraq and SE Turkey. Image from positivity.wordpress.com.

Figure 2. A picture from the SE border. Image from Milliyet.com.tr.

D. LITERATURE REVIEW

A literature review on border security, terrorist activities, and UAVs reveals that many students at NPS have studied similar problems using the simulation environment Map Aware Non Uniform Automata (MANA). Seven studies, four NPS student theses and three other research studies that address similar problems, are reviewed below.

In his thesis, Oh (2010) examines the border security problem of the ROK Army [20]. He develops a model in MANA to measure the time needed by an enemy to reach a waypoint and the probability of enemy mission failure. The results of his study provide insights on deciding a structure for border security.

The Department of the Prime Minister and Cabinet of New Zealand published the Maritime Patrol Review (MPR) in 2001. The review, which was driven by the planned $600M sensor system upgrade to the RNZAF's P-3 Orion maritime patrol aircraft, highlighted the poor state of maritime domain awareness in New Zealand in general and of maritime aerial surveillance in particular. Illegal fishing, drug smuggling, illegal immigration, terrorist activity, energy security, and transnational crime are some of the many threats to their maritime security. In his thesis, Oliver (2009) examines the effects of UAVs on New Zealand's maritime security and claims that UAVs provide a credible option to manned aircraft [21].

In his thesis, Yildiz (2009) explores the use of mini Unmanned Aerial Vehicles (mini UAVs) along with other assets to enhance border protection [22]. A part of the Tucson sector in Arizona is modeled in an agent-based model (MANA) for this purpose. The result of his study shows that the use of mini UAVs is useful in interdiction of illegal entrants and provides an enhancement of border security.

In his thesis, Sulewski (2005) analyzes the effect of UAVs in the Army's Future Combat Systems family of systems [23]. He builds a simulation model to determine how the numbers and the capabilities of UAVs affect a Future Force Combined Arms Battalion's (CAB's) ability to secure an objective. He conducts 46,440 computational experiments by varying many factors, including UAV capabilities. He finds that the UAVs, their capabilities, and tactics are significant factors on a CAB's performance.

In his study, Raffetto (2004) develops a model in MANA to analyze the effect of UAV characteristics on ISR missions for a Marine Expeditionary Brigade (MEB) commander in 2015 [24]. As a result, he contends that the UAV characteristics, such as airspeed, endurance, sweep width, and sensor capability are beneficial in terms of intelligence gathering.

Bertsche and Schwarz (2002) develop a model in MANA to analyze another scenario: "Protection of Stationary Potential Terrorist Targets" [25]. They state that agent-based models offer a better solution for modeling the problem where traditional operation research (OR) analysis is limited in explaining intangible factors such as persistence and courage. The results of their study yield significant results for the scenarios studied.

Butler's (2001) research report indicates that UAVs with advanced sensors are an integral part of Twenty-first Century ISR missions [13]. The results of the study show that the U.S Air Force should continue to use UAVs for

ISR missions and improve their sensor capabilities in accordance with rapid technological development.

THIS PAGE INTENTIONALLY LEFT BLANK

II. MANA

This chapter discusses the agent-based modeling platform Map Aware Non Uniform Automata (MANA), which is used for this study. First, we provide the definition and benefits of agent-based models. Second, we present the definition and evolution of advances in MANA, with several example studies. Finally, we explain why MANA is chosen as the modeling platform to conduct this study.

A. AGENT-BASED MODELING

Agent-based modeling and simulation (ABMS) has gained prominence lately with the growing interest in agent-based modeling, sophisticated modeling software, advanced computer technology, and the need for data. ABMS is used to model complex systems consisting of autonomous agents that interact with other agents and their environment. Sanchez and Thomas describe agent-based simulations as models in which multiple entities sense and stochastically respond to other agents and the conditions in their local environments, mimicking complex large scale system behavior [26]. In an agent-based model, autonomous decision making entities (which can be people, vehicles, ships, aircraft, animals, etc.) follow a set of predefined rules and algorithms that are coded based on personality weightings, movement algorithms, and penalty functions. Global behaviors then arise as a result of interactions of individual relationships.

The benefits of ABMS, over other modeling techniques, can be explained in the following three statements [27]:

1. ABMS captures emergent behaviors resulting from the interactions of individual entities.
2. ABMS is the most natural way of describing and simulating a system composed of “behavioral” entities. Agent behaviors can be represented explicitly within a range of options.
3. ABMS provides flexibility along multiple dimensions. One can use ABMS when the complexity is unknown and requires some effort.

Decision makers need detailed information on today's high technology products, many of which are costly to acquire. Modeling and simulation play a key role in gaining insights about these systems under limited budget and time when actual data is not available or limited. MANA-V (Map Aware Non-Uniform Automata-Vector), an agent-based distillation model [28] that is broadly used in military operations analysis, is used to model the border area in this study. Figure 3 provides the Terms-of-Use screen and general information about the developers and the version of MANA. The following sections provide an overview of MANA based mostly on the user's manual.

Figure 3. MANA terms-of-use screen.

B. EVOLUTION OF MANA

MANA is a stochastic, time-step software package designed to facilitate building and conducting combat simulations. MANA has been and continues to be developed by the Operations Analysis Section of New Zealand's Defense Technology Agency (DTA). DTA was inspired by the pioneering efforts of Ilachinski's agent-based models ISAAC and EINSTein [28]. These models helped DTA to see that a small scale, flexible model can be more suitable than a detailed simulation for the requirements of the New Zealand Defense Force (NZDF). Additionally, DTA realizes that automaton models can be used for analysis purposes. Nonetheless, DTA is well aware that they need to improve automaton style models to fully replace the older large scale models.

In 2000, DTA took the first step of improvement with the "Situational Awareness Map," using MATLAB. Afterwards, the programming language changed with the more flexible programming language Delphi. In general, MANA is designed as a scenario analysis model. Situational awareness, communication links, terrain map, waypoints, and event-driven personality changes are the strengths of MANA over most other agent-based models. The evolutionary steps of MANA are as follows [29].

1. MANA 2 (2002/2003)

As the first available version of MANA, this version forms the basis of ensuing models. MANA 2 consists of primary movement weightings, terrain editing features, sensor and weapon characteristics: simple cookie-cutter scheme or with tables of range-dependent probabilities, squad-based agent property definition, and shared situational awareness (SA) maps. SA maps can be used to model fundamental aspects of Network Centric Warfare (NCW).

Wolf (2003) used MANA version 2 to build his model about logistic support operations [30]. He analyzed the potential of ABMs for logistical decision making and mission success. He claims that ABMs are very useful in exploring highly complex scenarios.

2. MANA 3 (2003/2004)

A detailed NCW is possible in this version with an improvement to the squad SA map, communication links, and information sharing between agents. Supplemental movement algorithms allow agents to determine their movement based on information flow between other agents. Expanded data farming capabilities, special aircraft algorithms, and search algorithms are also introduced with this version.

Pfeiffer (2006) used MANA version 3.2.1 to exam the various factors that affect convoy missions in an urban environment [31]. He claims that MANA can produce useful insight even though it has limitations. Tiburcio (2005) utilizes MANA version 3.0.37 in his study of maritime protection of critical infrastructure assets in the Campeche Sound [32]. Cason (2004) developed a simulation model using MANA version 3 to reveal significant factors of UAVs in an urban infantry patrolling operation [33]. Aydin (2004) also conducts his study, "An Exploration Analysis of Village Search Operations," using MANA version 3.0. He investigates a village search operation that takes place in southeastern Turkey. He commends the efficiency of MANA "at exploring the factors affecting the non-linear nature of a search operation and the emergent behavior in low intensity conflicts" [34].

3. MANA 4 (2005/2006)

"Human-in-the-loop" studies are now possible with the new data streaming capability of this version. A battlefield zoom property, a genetic algorithm, a data analysis tool, finite sensor and weapon apertures, angular additions to the movement algorithms that include direction of facing, and squad formation shapes are the primary additional features of MANA version 4.

Oh (2010) utilizes MANA version 4 in his study on ROK Army border security problems because of the limitations in the alternatives [20]. Singham, Therkildsen, and Schruben use MANA version 4 in their analysis on flocking algorithms to input modeling for agent movement [35]. Yildiz (2009) develops a model using MANA version 4.04.1 for his study [22].

4. MANA 5 (2006/2013)

There is a conceptual change in this latest version. Grid-based movement algorithms, which are used in all previous versions of MANA, are now converted to vector based movement algorithms. Figure 3 provides insight into both approaches. In previous versions of MANA, agents in the battlefield move grid square to grid square in each time step depending on model set-up. The next grid that an agent is about to move can involve enemy, neutral, friendly units, and terrain features. The user defined personalities constitute the basis of agent behaviors.

In the latest version, agents in the battlefield calculate a vector, such as $F_{E,}$ $F_{T,}$ F_W given in Figure 4, toward all other entities of interest and terrain within sensor range or depending on information provided by inorganic contacts. The product of these vectors and the personality weightings generate the final vector. The agent movement is calculated based on Newton's second law and standard kinematic equations for constant acceleration.

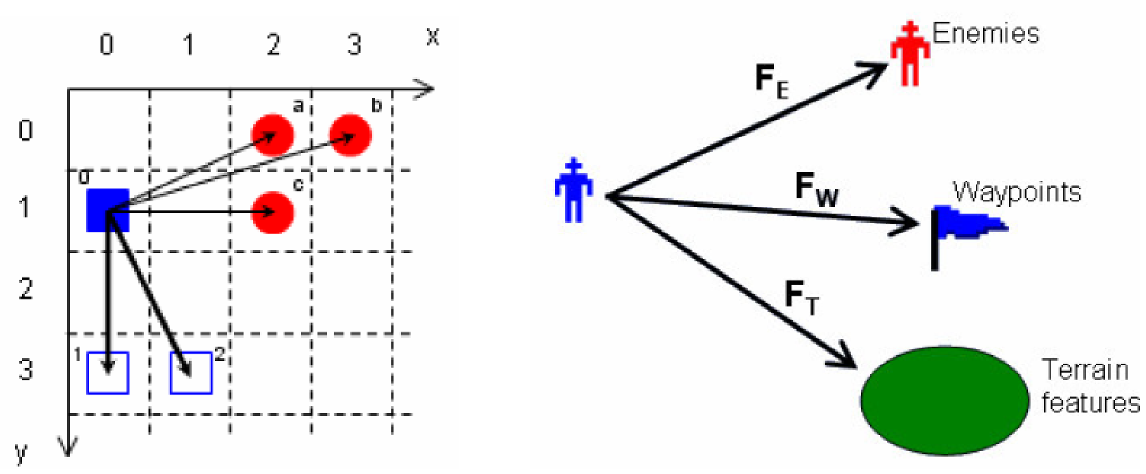


Figure 4. Two different approaches to calculate movement: The grid-based (right), the vector based (left) (From: MANA user manual).

The advantages of vector based algorithms are explained in the MANA user manual as follows:

1. Larger battlefields can be modeled.
2. Battlefield region, agents speeds, sensor, and weapon characteristics can be defined in terms of real world units. Therefore, MANA users no longer have to convert real-world units to model units.
3. New features can be easily added to models and scenarios.

The rest of the model properties remain almost unchanged. Therefore, the developers publish the MANA-V user manual as a supplementary document to the MANA 4 user manual.

C. WHY MANA

MANA version 5.01.03 is chosen as the modeling tool to support this research. In MANA, agents are aware of their local environment, terrain, and battlefield activities. Agent behaviors are determined based on their activities, goals, and terrain type. However, all agents are not necessarily reacting in the same manner. They respond to events according to personality weightings and information provided by organic and/or inorganic SA maps.

MANA requires a shorter training period than most other comparable modeling environments. The simple graphical user interface (GUI) allows users to build scenarios in a short time period. Furthermore, MANA has an “on-the-fly” editing capability. Users can edit scenarios at the time updates are needed. Primarily, analysts prefer MANA because of their limited time to grasp dynamics of the real life situations for programming into higher resolution models.

Agent behaviors in MANA are controlled by decision making algorithms. Therefore, agents react based on personalities, not orders. The interaction of agents can be analyzed in MANA. Agents may change their personalities as a result of triggering events. Built-in data farming capabilities allow users to readily explore parameter variables in their model.

Unlike other highly detailed agent-based models, MANA reflects only the essential details of a scenario. “It is a myth that a more detailed model is necessarily a better model, because it is impossible to capture accurately every aspect of nature” [28]. The more complex a model is the less transparent it is. Hence, it would be difficult to model local relationships of this geography based analysis and to reveal interactions between factors using a conventional model.

THIS PAGE INTENTIONALLY LEFT BLANK

III. SCENARIO AND MODEL DEVOLOPMENT

"All models are wrong, but some are useful."

–George Box

In this chapter, we provide detailed information on scenario and model development. First, we explain a real-life skirmish that motivates the baseline scenario analyzed in this study. Second, we cover all models developed based on this skirmish. Third, we describe the battlefield and terrain features. Finally, we introduce the agents in the model.

A. SCENARIO

The baseline scenario analyzed in this research is based on a skirmish between a guerilla team and a Turkish battalion in the Southeast region of Turkey. In October 2007, an estimated 150 to 200 terrorists attacked an infantry battalion located near the Southeast border of Turkey with Iraq. The nearest friendly force was situated 5.5km directly behind the attacked battalion. Because of the hard terrain, the two battalions were connected to each other via a bridge, which was the only way of land transport, over a river.

Using information from news reports of the attack, the Blue forces, which represent the friendly side in this scenario, are composed of 50 infantrymen, two cannons, rocket projectors, and grenades. The commander positions the personnel to watch the area for terrorist activity. Figure 5 depicts a picture of the attacked battalion. Field-of-vision is a major problem when considering the rugged characteristic of the province, especially during the night. The Red forces, which represent the terrorists, are composed of 150 to 200 guerillas equipped with grenades, bazookas, and other small arms. The terrorists split into three groups. Two of the groups carry out missions before commencement of the main assault. The purpose of the remaining terrorists is to directly attack the battalion. The Blue forces are well trained and equipped, but the Red side has the advantage of easy adaptation to rough terrain. The terrorists use the terrain to increase their effectiveness. Additionally, the Blue side has no intelligence about the attack, so the terrorists have the advantage of surprise.

Figure 5. A view of the attacked battalion (From: Haberler.com).

The Red side conducts reconnaissance activities to gather necessary information and intelligence about the region and Blue forces, and plan their attack based on this information. The length of the pre-attack period mostly depends on the infiltrators, who stay covered all the time and act as neutral parties. Since the Red commander wants to ensure the success of the attack, he assigns three of his subordinates as a leader for each group. Following the planning step, the guerilla team enters Turkey through the northern Iraq border around 2330. They split into groups as planned, and the first group of 10 guerillas goes to the village and cuts the electricity and telephone lines before commencement of the attack. The second group of 20 guerillas blows up the only bridge to the outpost. Then, these two groups combine into a single team to stop or delay any reinforcement. Meanwhile, the third group proceeds to their initial position. Once they take position, four of the terrorists form a recon team and start close defensive fire at around 0200 to reveal the location of the battalion so that the attackers located on another mountain across from the battalion can aim their shots. One of the critical issues for the Red side is time. In general, guerilla teams avoid long engagements. But, in this case, they are well-prepared and outnumber the isolated Blue side by a factor of four. So, the plan is to overrun the outpost before reinforcements arrive. Conversely, the Blue side tries to stay close, with a minimum of friendly losses, to keep coordination and communication as effective as possible, and to hinder the Red side from capturing the battalion.

The salient point of the summary is the Blue force's lack of intelligence and detection until Red attacks. This study of the baseline scenario focuses on detection of Red members before they cross the border or before they reach their attack points. Therefore, no skirmish between the Red and Blue sides is explicitly modeled. For this purpose, five different versions of the scenario are analyzed to derive the effectiveness of Unmanned Aerial Vehicles (UAVs) (from 0 up to 4) assigned over the area of interest.

1. Baseline Scenario

This scenario is based on the skirmish explained above. This baseline scenario includes all of the agents except UAVs. There are 150 terrorists, divided in four groups, which try to cross the border and make their way to their attack positions. Initial runs of the baseline scenario help us quantify how many of the Red Agents will reach the final waypoint without UAV detection, as in reality, during the predefined maximum time limit. Even though Scouts, Civilians, and a Blue Killing Agent exist in the scenario, they do not have any effect on the result for this specific scenario.

2. Scenario Two

There is only one area of responsibility (AOR) and one UAV in this scenario. This is the extension of the baseline scenario with one UAV over the whole area of interest. The screenshot in Figure 6 depicts the placement of one UAV and the other agents. The terrain types are modeled using different colors. The roads are colored as yellow. The dark brown and light brown colors represent the mountains and off-road areas. We add a grey colored layer to the terrain to facilitate visualization of the border region.

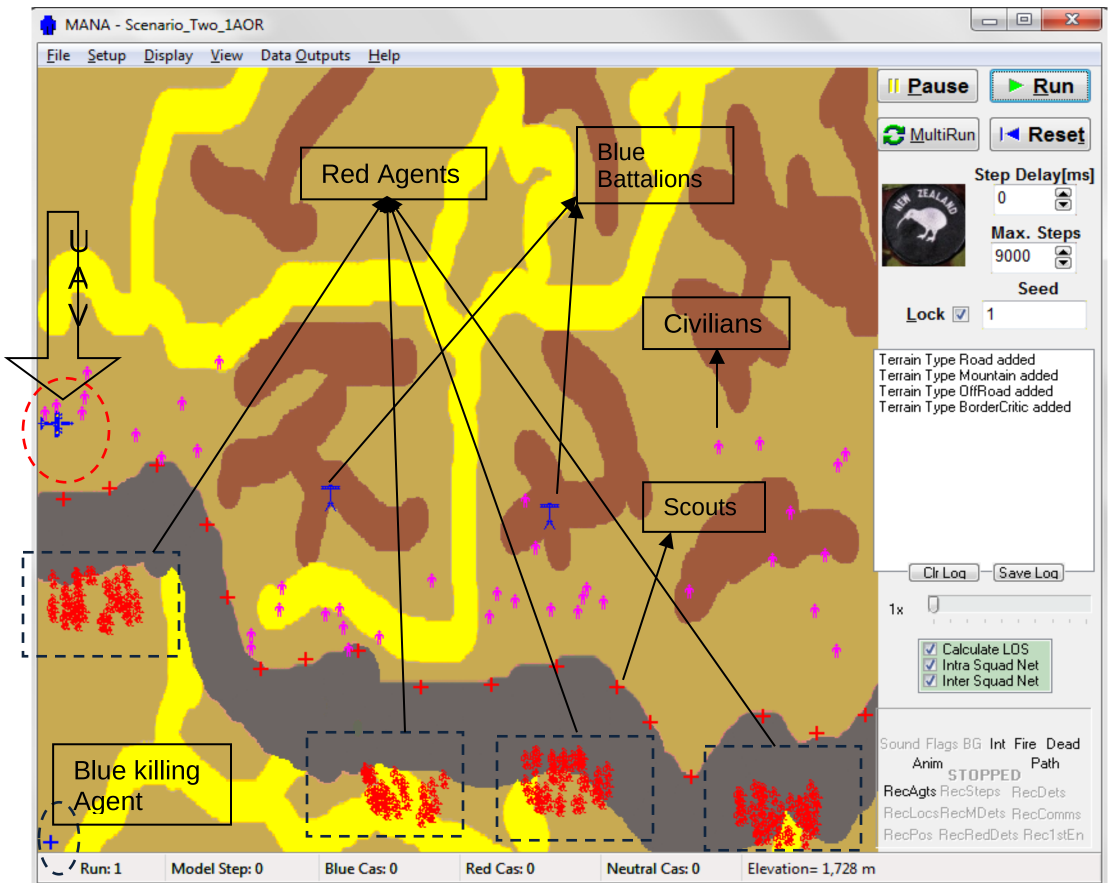


Figure 6. Scenario two developed using MANA.

3. Scenario Three

The baseline scenario was again updated, this time adding two AORs and two UAVs over the region. As in the second extension of the baseline scenario, the third scenario allows us to see how the number of Blue and Red casualties changes depending on the number of UAVs, two in this case. The screenshot in Figure 7 shows the position of the two UAVs, based on the AORs, and the other agents.

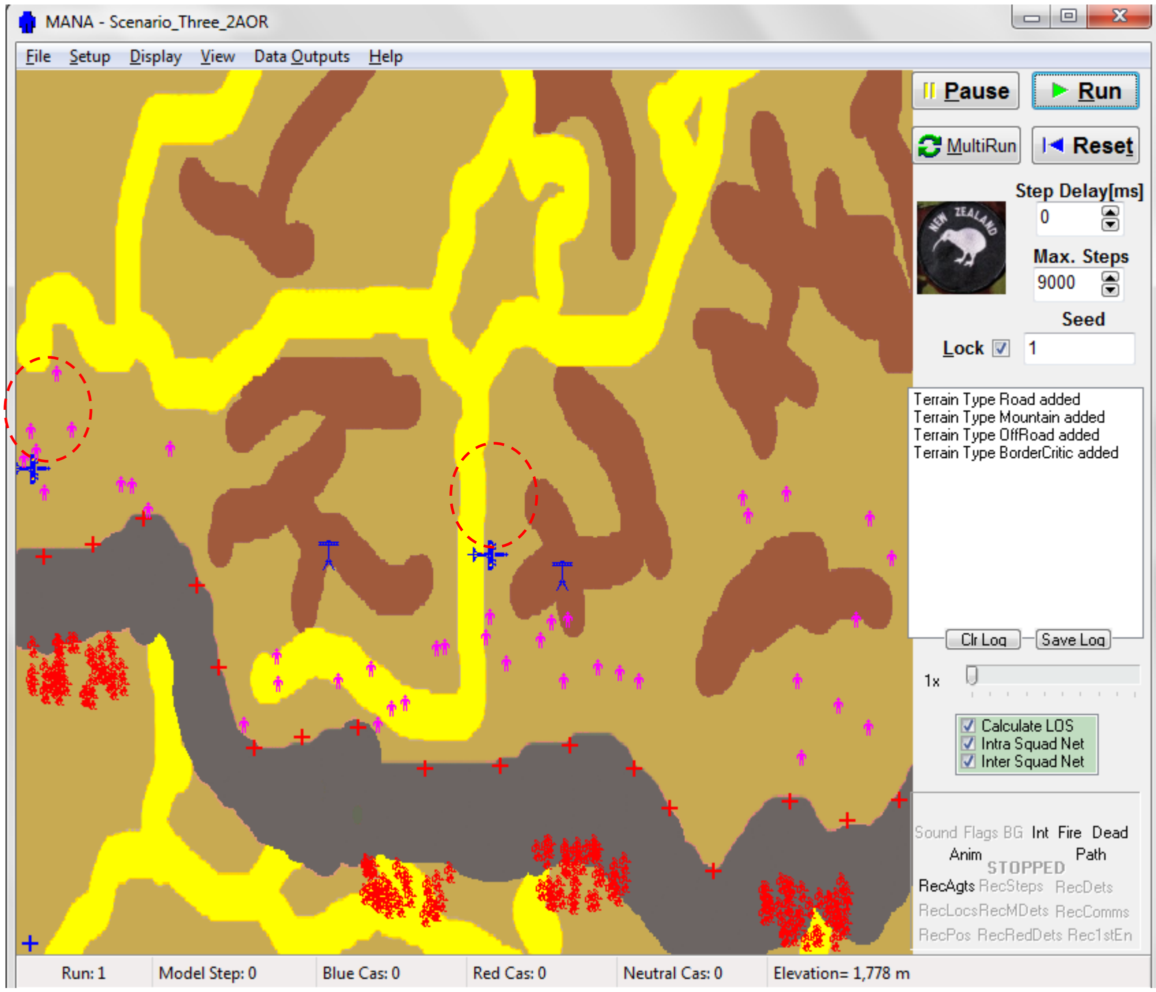


Figure 7. Scenario three developed using MANA.

4. Scenario Four

Scenario four, the fourth updated version of the baseline scenario, consists of three AORs and three UAVs. There are no other differences between the scenarios in terms of agent placement or parameter and factor set up. This scenario allows us to see the effect of three UAVs, shown in Figure 8, on the results.

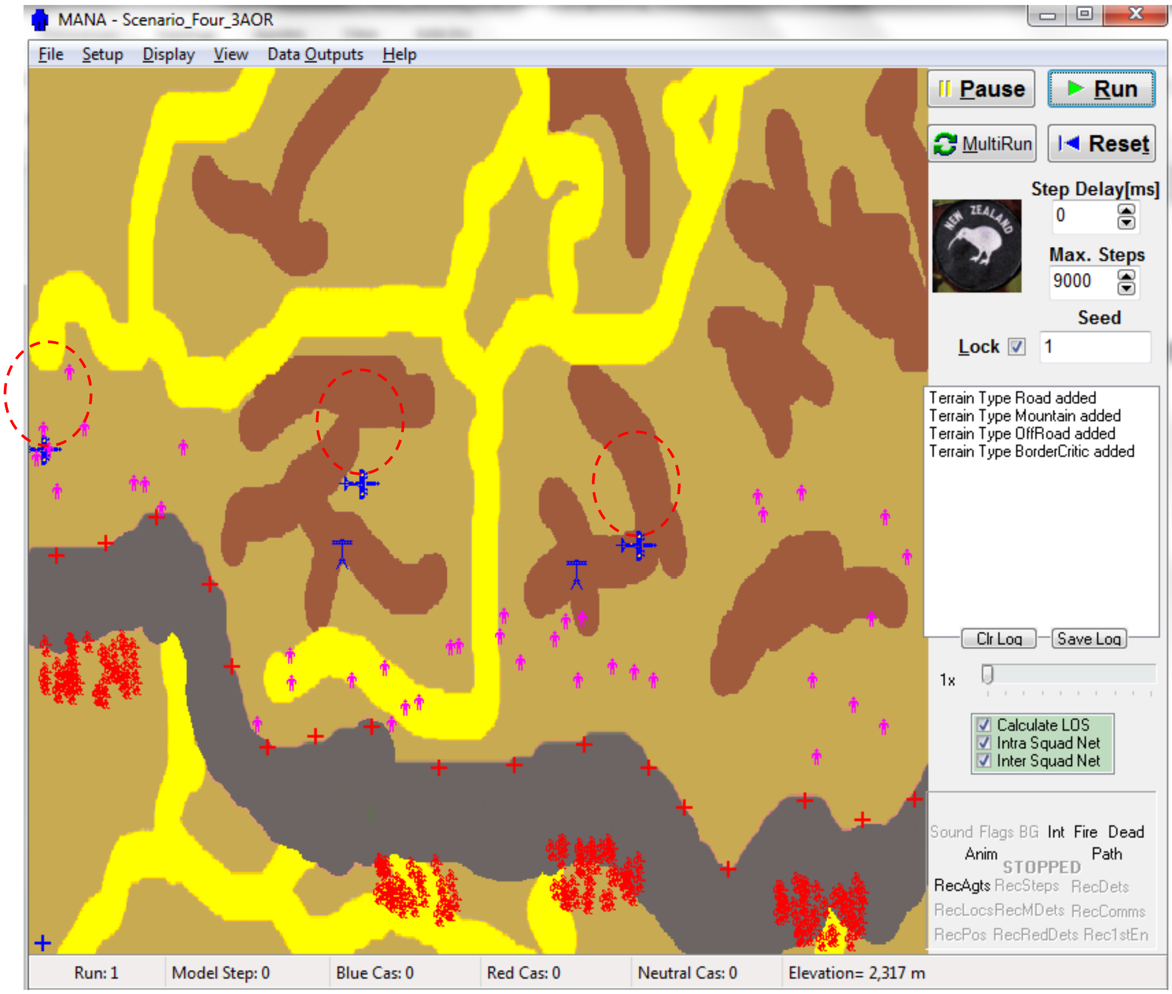


Figure 8. Scenario four developed using MANA.

5. Scenario Five

As the final extended version of the baseline scenario, the fifth scenario, comprises four AORs and four UAVs. The only difference between the modified scenarios and baseline scenario is the number of AORs and the number of UAVs. The purpose of Scenarios Two though Five is to see how the outcome of the model changes with the number of UAVs. Therefore, all other aspects of the model, including the design of experiment, are kept constant. The screen capture in Figure 9 displays the positions of UAVs on the battlefield for this scenario.

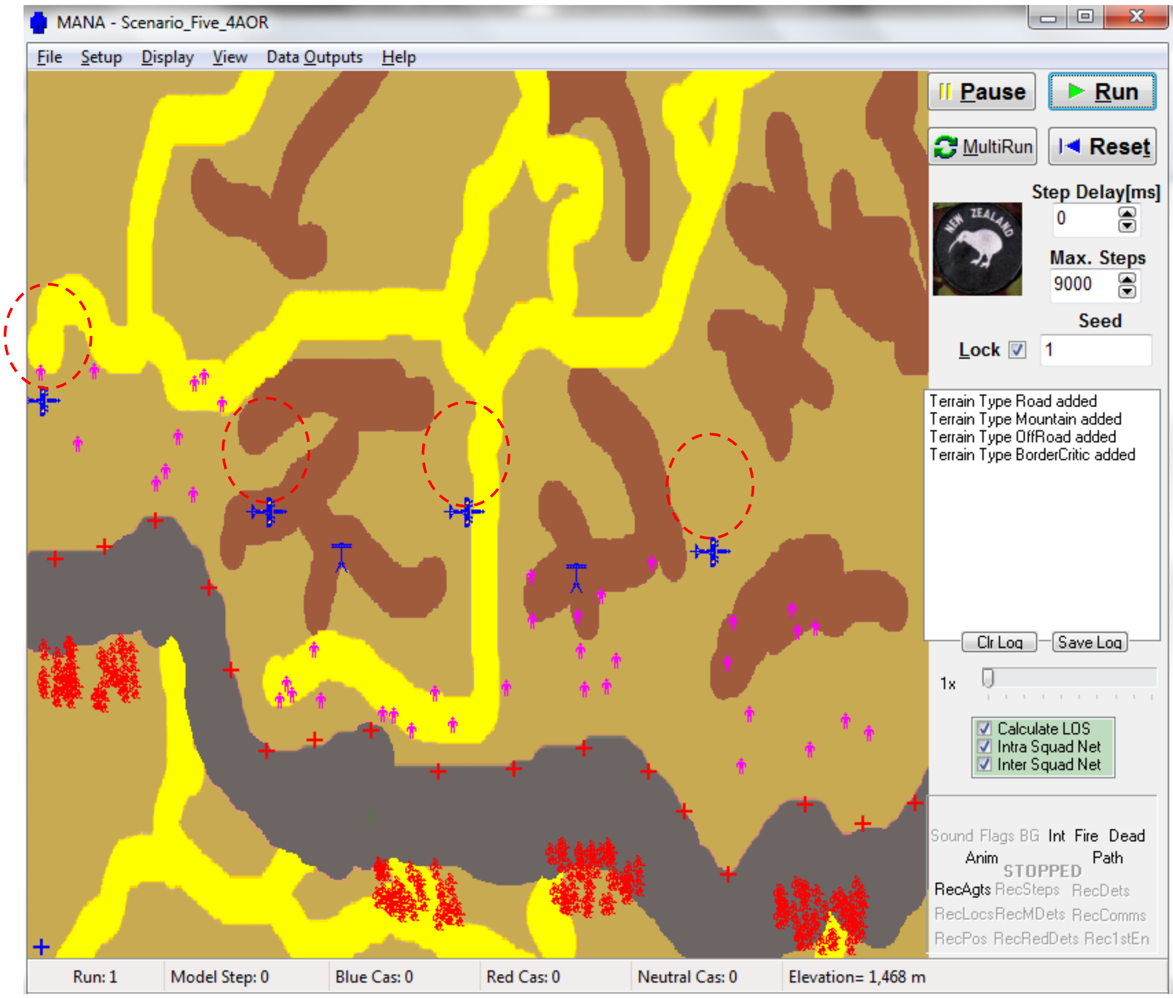


Figure 9. Scenario five developed using MANA.

B. BATTLEFIELD

In MANA, the battlefield is a bounded area on which all entities are placed. For this study, the battlefield represents an 87 x 108 km border region in the Southeast part of Turkey. Battlefield distances, sensor ranges, and weapon ranges are defined continuously in terms of real world units (meters).

The battlefield consists of three types of maps: Background, Terrain, and Elevation maps. The background map is used on top of the battlefield for cosmetic purposes to improve visualization of the scenario. The background map has no effect on going, concealment, and cover. The terrain map includes terrain features for each terrain type used in the model, such as roads, mountains, etc., that agents can follow and use for concealment or cover. Three different RGB color codes are used to define each terrain type. Terrain types have distinctive characteristics in terms of going, concealment, and cover. Possible going, concealment, and cover values range from 0.0 to 1.0 and affect agents' speed, sensor capability for detection and classification, as well as terrain protection from weapon fires, respectively. Terrain map and terrain features are provided in Figure 10.

	Going	Cover	Concealment	Red	Green	Bue	Color
Road	0.90	0.00	0.00	225	225	0	
Mountain	0.10	0.70	0.90	160	90	60	
Off_Road	0.60	0.40	0.80	200	170	82	
Border_Critic	0.60	0.30	1.00	108	101	99	

Figure 10. Terrain map and terrain features.

The elevation map, which consists of greyscale colors, is used to define elevation features of the terrain. For this study, the real world elevation range is defined from 640 meters to 3185 meters. The elevation map used in this study is depicted in Figure 11. The white and black colors in the elevation map represent the highest and lowest point of the region respectively. In the terrain map, the white areas are formed as mountains. Terrain and elevation maps affect the speed and LOS calculations of the agents. The multipliers given for the terrain types are used when computing the movement speed, sensor detection associated with the concealment factor, and hit rate that affects the shot probabilities. The LOS is calculated based on the sensor height of each agent and elevation ranges defined for the elevation map.

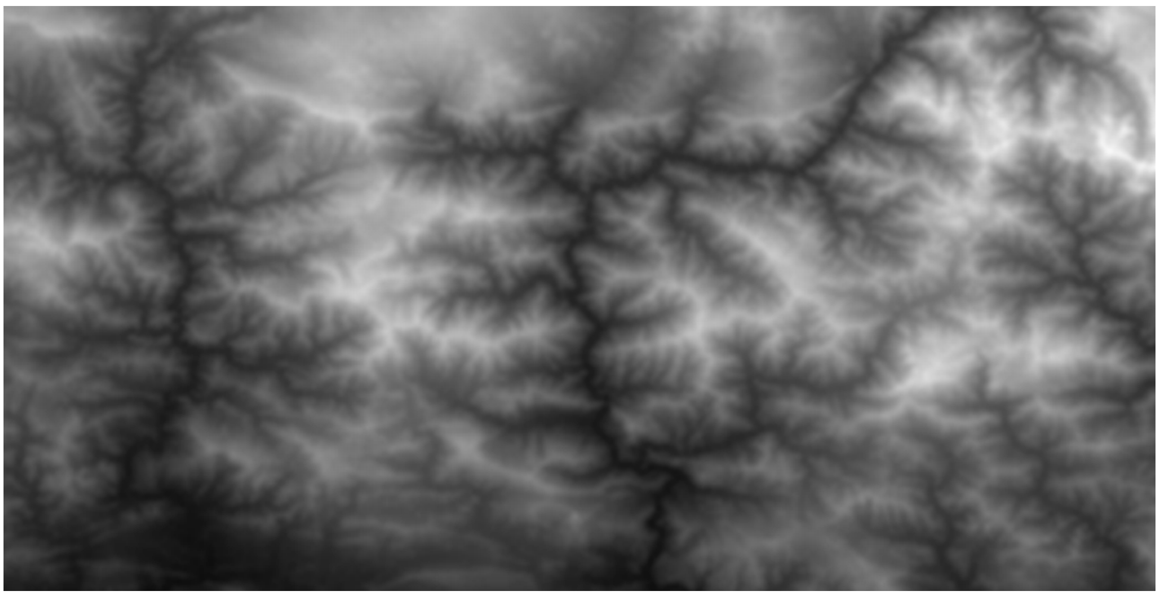


Figure 11. Elevation map.

The elevation data is downloaded from the EarthExplorer website, in Digital Elevation Model (DEM) format. The elevation range changes between 640 meters to 3185 meters. Then, the ArcMap, a part of the ArcGIS toolbox, is used to view the elevation data, mark off the desired play box, make note of the highest and lowest points of elevation, and export a picture of it. Finally, Paint.Net is used to convert the picture to bitmap (BMP) format and resize it so that it will allow adequate resolution for the selected play board.

The ArcMap and EarthExplorer are again used to acquire different views of the terrain to support the creation of the terrain map. Paint.Net and Adobe Photoshop CS6 software are used to generate layers for different terrain types. The final product is flattened into a BMP image that MANA understands.

The time step of all the simulation runs is set at five seconds. Initially, the entire model was developed using a time step of one second. A time step of one took too long to run. Therefore, experiments were conducted with the values three, five, and ten to see how the model runs with these time steps. The model runs show that a time step of ten seconds is an ineffectual candidate because it causes the model to change states in an unexplained pattern. So, to avoid incorrect results, a time step of five seconds is selected. However, the model still requires plenty of time for a complete run. Consequently, the maximum time step is defined as 9000 time steps. This corresponds to twelve and a half hours in real life. The baseline model yields that this number is adequate for half of the Red members, on average, to reach their final waypoints.

While dealing with the time step, it was found that time in “Fuel Out” state is not defined in terms of seconds as stated in the “Edit Squad Properties” panel and user’s manual. In fact, the duration in this state is defined as time steps. Additionally, the first two seconds of “Spare 1” state, which is used for refueling purposes in this study, is ignored and refueling starts at the third second. (These problems have been reported to the developers.)

C. AGENT DESCRIPTIONS

Squads constitute the key unit of Map Aware Non Uniform Automata (MANA). The maximum number of squads in a scenario is 32,767. The number of agents in a squad can be between 1 and 1000. There are 13 squads in this study, as shown in Table 1.

Table 1. Agents and features.

Squad	Name	Allegiance	Threat level	Class
1	Blue_UAV1	1	3	1
2	Blue_UAV2	1	3	1
3	Blue_UAV3	1	3	1
4	Blue_UAV4	1	3	1
5	Blue Battalion	1	3	0
6	Red_Team1	2	3	2
7	Red_Team2	2	3	2
8	Red_Team3	2	3	2
9	Red_Team4	2	3	2
10	Red Scouts	2	3	3
11	Civilians (Neutrals)	0	2	4
12	Blue Killing Agent	1	3	5
13	Blue Targets	1	2	6

The allegiance represents the agent's side in the battle. The allegiance of an agent can be friend, enemy, or neutral. Threat levels and class parameters are used to define different types of agents in a scenario. For example, UAVs and Blue Killing Agent are allied, but they are equipped differently, and their task in the scenario is also different. So, threat levels and class parameters help distinguish these agents in the scenario.

The placement of agents onto the battle field is shown in Figure 12. The Red Team, divided in four groups, starts on the Iraq side of the border. Scouts are located along the border so that they can provide information on UAV activities. The Civilians are distributed around the battlefield. Each UAV, which is responsible for predefined area of responsibility, is defined as an airborne sensor.

Figure 12. Overview of battlefield with all agents.

1. Blue UAVs

Blue UAVs are responsible for monitoring the 87 km border, which is divided into AORs (from 0 up to 4). The personality weightings and trigger states for UAVs are shown in Figure 13. The personality weightings are set using a slide bar and can take values between -100 and 100. Positive values indicate a positive propensity towards the associated personality, while negative values indicate a negative propensity. Personality settings other than the default value of zero are shown in red. To ensure that UAVs will not engage the same group of Red Agent, personality weightings towards friends are set to -100 in all states. At the beginning of each model run, UAVs directly fall into the run start state, which allows UAVs to start patrolling at random and different times. Each UAV is capable of detecting, classifying, and tracking illegal entrants. A UAV follows predefined waypoints in the default state. Once it detects an activity, it then proceeds to the detection area for classification. The UAV tracks the classified agent if it is a Red Agent and sends the information to the Blue Killing Agent. Otherwise, the UAV keeps following its waypoints.

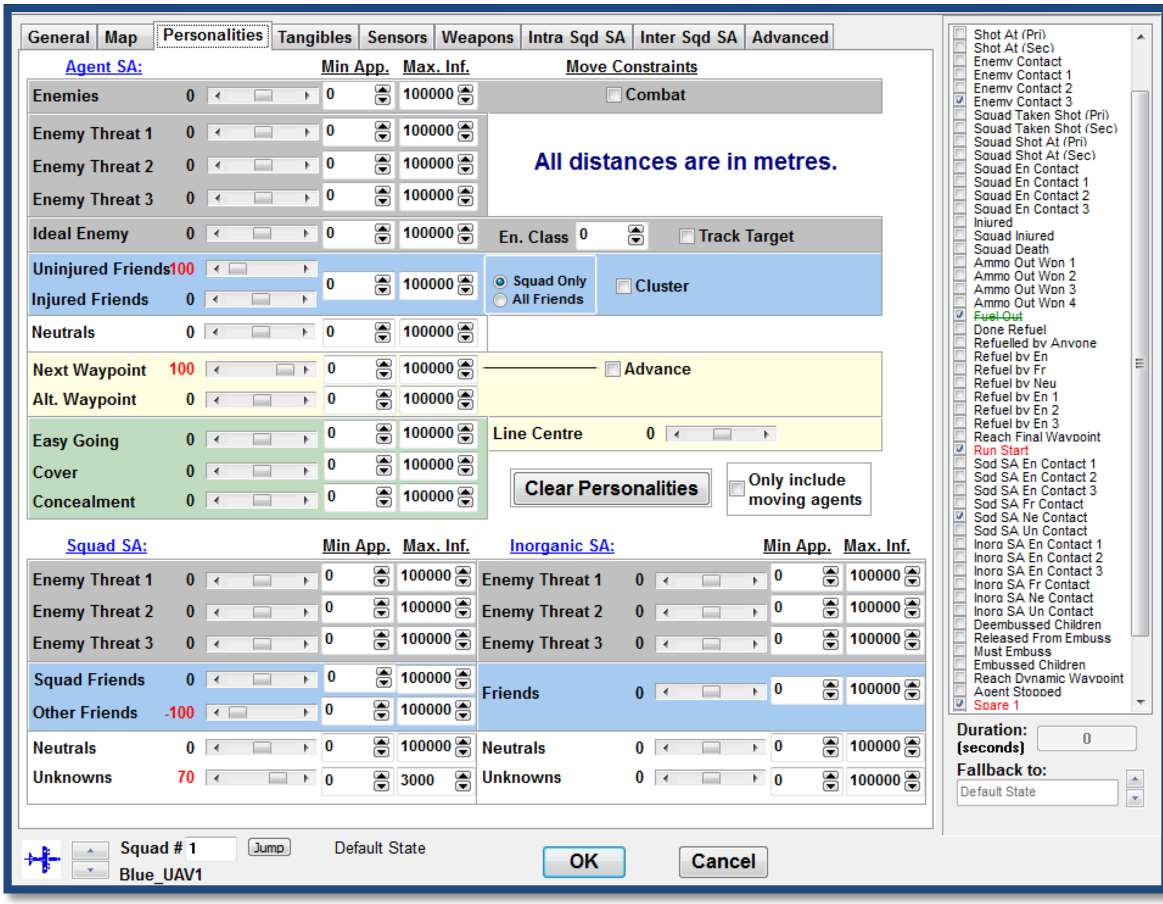


Figure 13. Blue UAV squad personalities and trigger states.

The Inorganic Squad SA panel controls the flow of information among the squads. The communication link parameters are invariant within the trigger states. UAVs have a communication capability with the Blue Killing Agent as shown in Figure 14. To prevent multiple detections, the communication latency parameter is set to zero.

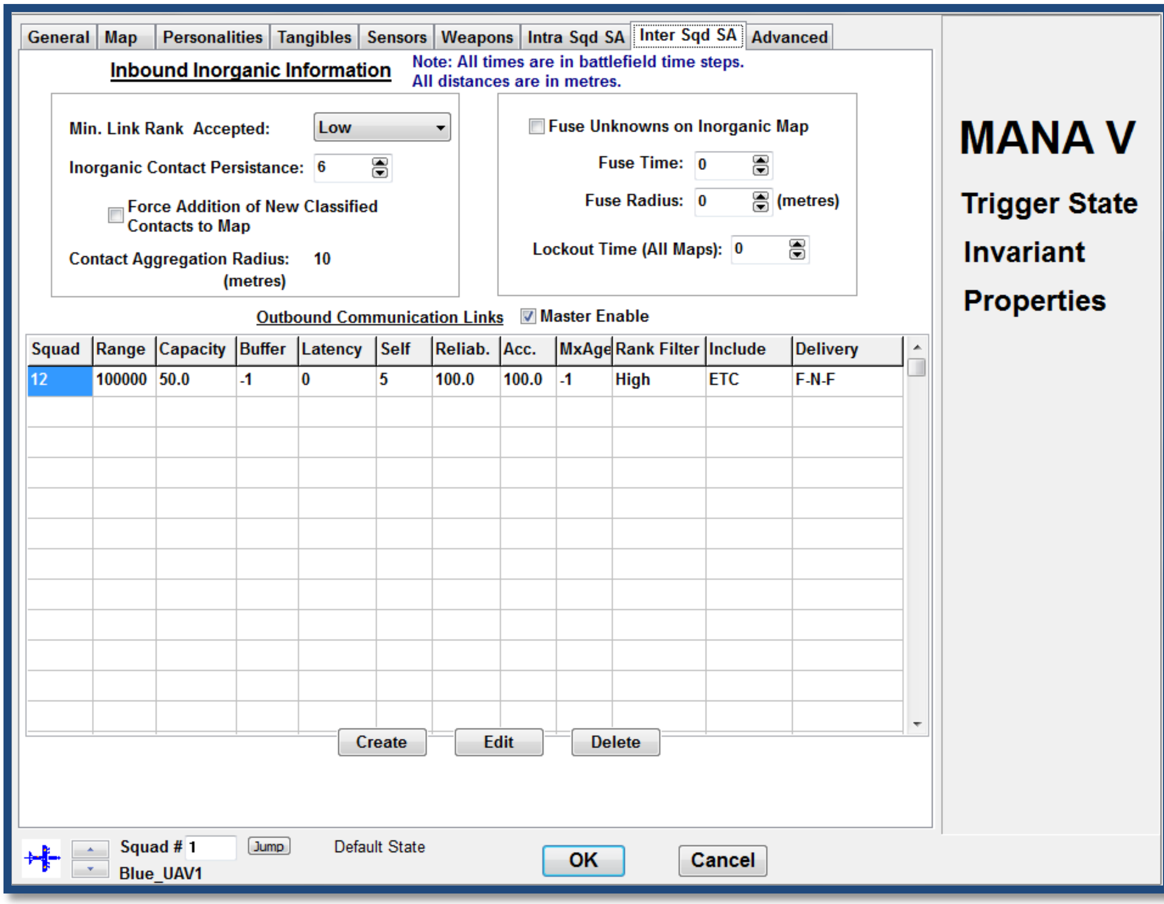


Figure 14. Blue UAV inorganic SA communication link parameters.

There is no specific refueling strategy for the UAVs. When low on fuel, they jump into the "Fuel Out" state and go to their alternative waypoint for refueling. UAVs have a strong propensity to go directly to their alternative waypoint in Fuel Out state (Alternative Waypoint weighting is set to 100). The refueling state has the highest priority. Therefore, UAVs cannot be interrupted by any other activity.

2. Blue Battalions

There are two Blue Battalions, which provide final waypoints for Red Agents. The final waypoints for the Red Agents are set depending on the location of the battalions.

3. Red Teams

Red Teams represent the terrorists. There are four groups of Red Teams trying to cross the border. The personality weightings and trigger states are shown in Figure 15. Initially, each group is located at four different points along the Iraq side of the border. The Red Teams are the most valuable target, with a threat level of three. They follow their waypoints into Turkey and try to avoid UAVs along their path. They have a strong negative propensity towards UAVs (Enemy Threat 3 weighting is set to -100) and a desire for concealment.

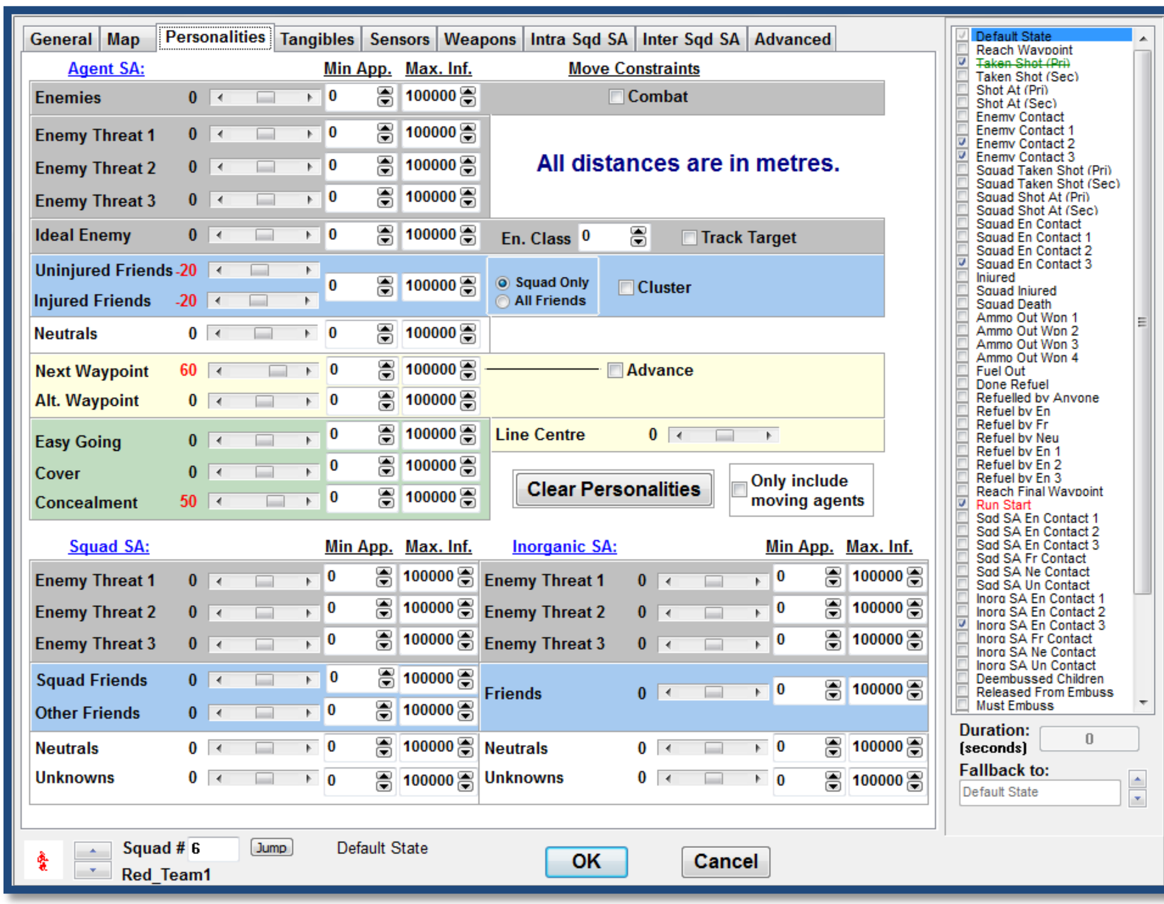


Figure 15. Red Agents squad personalities and trigger states.

Red Agents have no communication capability with other agents, but they can get information on UAV activities via Scouts in the base model and via Scouts and Civilians in the additional scenarios. Once Red Agents are classified by UAVs, they are devolved to the Blue Killing Agent.

Red Agents increase their concealment value to 100% in all enemy contact states except for the Enemy Contact 2 state in which they make contact with Blue Targets. The experience of terrorist teams and the harsh terrain of the region allow terrorists to have a perfect stealth value in most cases. This higher concealment value allows us to see the effectiveness of UAVs in worst case conditions. Once they reach the final waypoint, each Red Agent kills one Blue Target and becomes invisible so as not to be detected and killed. This allows us to count how many terrorists reach their destination undetected in the allotted time.

Each Red Agent has a weapon that can fire within a range of 600 meters. The Red Agent's weapon parameters are set as in Figure 16. The amount of ammunition for each weapon is set to one to ensure that each Red Agent, who reaches the final waypoint, will kill only one Blue Target. Civilians, UAVs, and Blue Killing Agent are selected as non-target classes to prevent the Red Agent from firing on these agents and consuming their ammunition. In this model, attrition is used only to record how many Red Agents are detected by a UAV prior to reaching their destinations and how many make it to their destinations undetected.

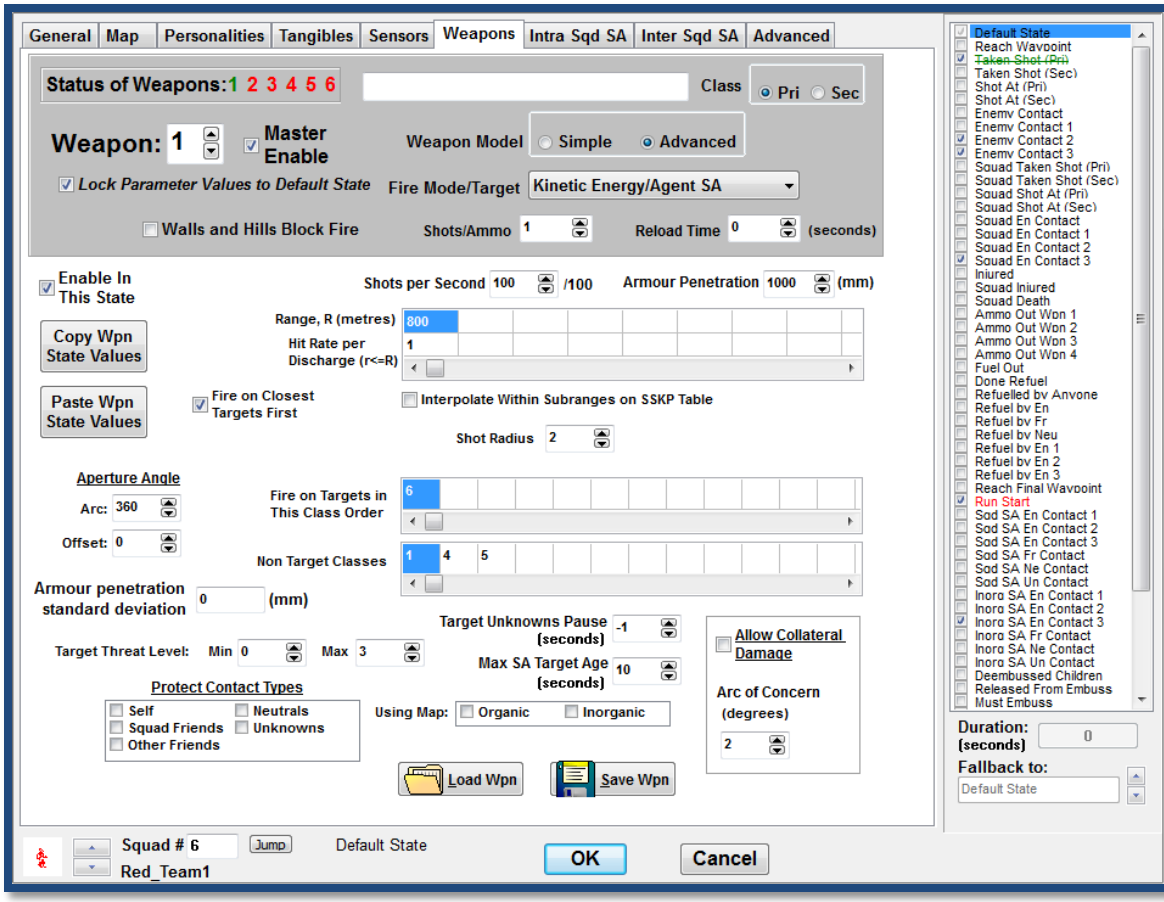


Figure 16. Red Agents weapon settings.

4. Scouts

There are 17 Scouts, who are invisible to all other entities on the battlefield, distributed along the border to provide information about UAV activities to the Red Teams. Scouts have a stationary observation point. They are able to extend their sensor range by using binoculars. The inorganic SA communication links for Scouts are shown in Figure 17. Scouts can communicate with Red Teams to provide information on UAV activities.

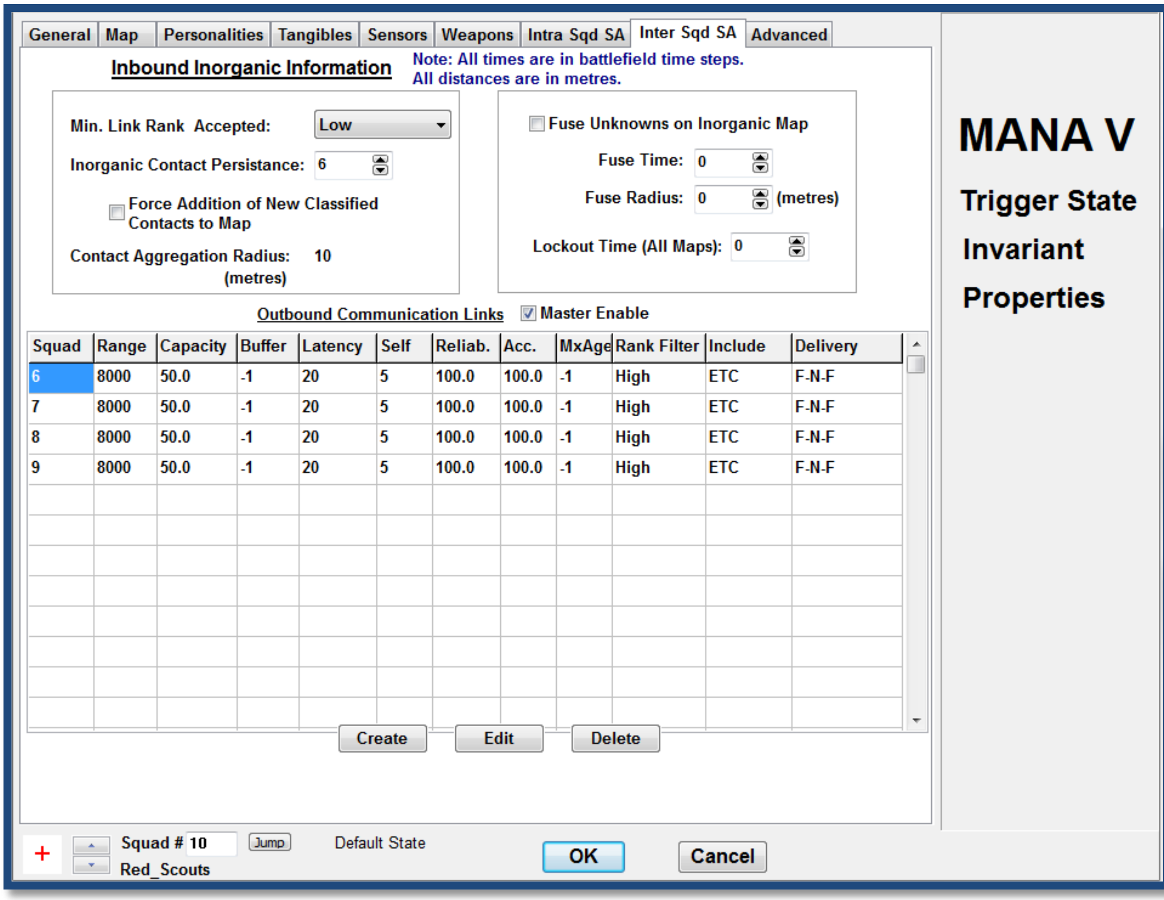


Figure 17. Scouts inorganic SA communication link parameters.

5. Neutrals

Neutrals are distributed around the battlefield and given some waypoints inside the AOR of UAVs. Having a threat level of two, they are not as valuable as Red Agents. Neutrals are the agents that cause distraction to the UAVs until they are classified as neutral in the base model. However, they can provide information on UAV activities to the Red Agents in some scenarios. In these scenarios, Neutrals communicate with Red Agents over a radio and take the roles of distractor and infiltrator.

6. Blue Killing Agent

There is one Blue Killing Agent that takes classified Red Agents out of action. The Blue Killing Agent has a perfect concealment value and remains invisible during the whole scenario. In reality, the information on terrorist activities, provided by UAVs, will be transferred to another security unit. Current border security architecture does not include UAVs. All information going to the Blue Killing Agent flows through the UAVs. Therefore, this agent is used to disregard classified Red Agents to avoid counting multiple detections of the same Red Agent. The Killing Agent has a perfectly accurate weapon so that it can kill a classified Red Agent with one shot. The weapon parameters are shown in Figure 18. The weapon fire range is set to 100,000 meters. Red Agents and Scouts are selected as target classes. The Blue Killing Agent is a modeling tool that kills Red Agents depending on the information provided by UAVs.

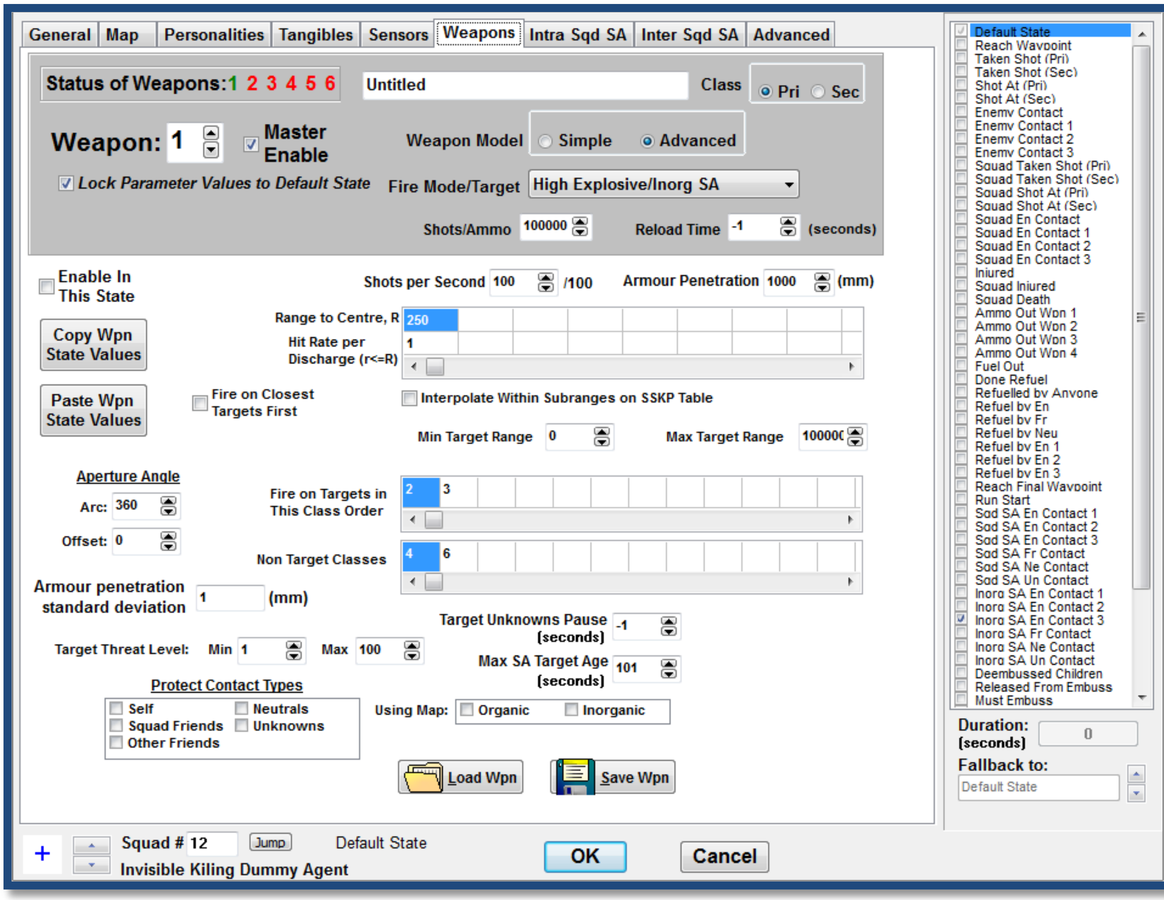


Figure 18. Blue Killing Agent weapon settings.

7. Blue Targets

There are four groups of Blue Targets, each with the same number of agents as the Red Teams. The Blue Targets are located at the final waypoints of the Red Teams. The icon type for this squad is set as zero. Thus, they cannot be seen by the users, but they are visible to all battlefield agents. Having a threat level of two, they are not a real threat for the Red Agents. They do not have any weapons and do not resist Red Agents. Each Blue Target is killed by one Red Agent, who has only one bullet. The number of killed Blue Targets forms a surrogate for the number of Red Agents who can reach their final waypoint. There are 150 terrorists in total, and there will be undetected terrorists who cannot reach the final waypoint at the end of predefined maximum time limit. Hence, this squad is required to count the number of terrorists who can reach the final waypoint.

THIS PAGE IS INTENTIONALLY LEFT BLANK

IV. DESIGN OF EXPERIMENTS AND MODEL RUNS

Design of experiment (DOE) techniques allow for obtaining individual and interactive effects of factors that affect the results. DOE enables a robust design by providing full insight into interactions between design factors. Therefore, DOE plays a key role in data collection through simulation runs. In this chapter, we discuss the factors and levels which form the experimental design of our study. Additionally, we explain the tools and techniques used to automatically run the model given the experimental design on the Simulation Experiments and Efficient Design (SEED) Center's (http://harvest.nps.edu) computing cluster. Finally, we provide an analysis of model run time given our design.

A. FACTORS AND LEVELS

A wide range of factors can be varied by the design to examine their effects on the outcome. The factor ranges were selected to cover the capabilities of existing UAVs. However, it is practically impossible to examine every possible factor and all of their combinations. Therefore, we conduct our analysis for a subset of factors that is thought to be most influential on the response. Table 2 provides the factors and their levels that are used in the experimental design.

In addition to the factors varied in the design, there are also 13 dependent input variables that are set as a function of some of the factors. MANA allows users to choose two modes (advanced and cookie cutter) for the sensors. While modeling UAVs in the model, "advanced mode" is used for their sensors. Therefore, three levels of ranges, time between detection, and their corresponding probabilities are defined rather than using only one level. Medium and minimum classification ranges are calculated by multiplying maximum range, which is explicitly varied in the design, by 3/5 and 1/5. Similarly, medium and minimum range classification probabilities are calculated by multiplying maximum range classification probability by 2/3 and 1/3. The time between detections for medium and minimum levels are set by multiplying maximum time between detections by 2/3 and 1/3. Finally, fuel usage rate in refueling state is computed by multiplying initial fuel level by 1/5. The list of dependent variables which form design points with factors varied into the design (independent variables) is provided in Appendix A.

Table 2. Factors that are varied in the experimental design and their ranges.

	Factor Name	High Level	Low Level	Unit	Type of Variable
UAV	Speed in Default State	450	90	km/hr.	continuous
	Speed in Enemy Contact State	300	60	km/hr.	continuous
	Height in Default State	5000	2000	M	continuous
	Height in Enemy Contact State	4000	1000	M	continuous
	Classification Range in Default State (Max.)	10000	1000	m	continuous
	Classification Range in Enemy Contact State (Max.)	10000	1000	m	continuous
	Probability of Classification at Max. Range in Default State	0.264	0.04		continuous
	Probability of Classification at Max. Range in Enemy Contact State	0.33	0.05		continuous
	Time Between Detection at Default State (Max.)	180	15	seconds	continuous
	Time Between Detection at Enemy Contact State (Max.)	120	15	seconds	continuous
	Fuel Level	21600	2700	seconds	continuous
	Time Step in Refueling State	7200	1800	unit	continuous
		1440	360	Time steps	
	Slew Rate in Enemy Contact State	90	20	degrees (per second)	continuous
Scout	Sensor Range	3000	600	m	continuous
	Communication Range With Red Team	5000	500	m	continuous
	Communication Latency With Red Team	20	6	Time Step	continuous
Red Team	Sensor Range	3000	200	m	continuous
	Intra-Squad Communication Delays	12	6	Time Step	continuous
Civilian	Communication Link Exist	1	0	(Bernoulli)	categorical
	Communication Range With Red Team	10000	1000	m	continuous
	Communication Latency With Red Team	36	12	Time Step	continuous

1. Controllable Factors

Factors can be classified as either controllable or uncontrollable. Controllable factors can be controlled by the systems developers or operators—such as the number of UAVs used. They are easy to handle and investigate. In our study, controllable factors are the Unmanned Aerial Vehicle (UAV) parameters that might affect the UAVs' detection and classification abilities. The list of factors associated with UAVs, which are given in Table 2, constitutes the controllable factors for this study. Even though the number of UAVs is not directly included in the design sheet, it is one of the controllable factors. An experimental design is developed for a given scenario, and the whole design is crossed with the number of UAVs (1 up to 4). The number of UAVs assigned over the area of interest affects the mean coverage ratio over time. Similarly, speed, fuel level, and altitude of a UAV impact on the area covered and the endurance. Detection range, time between detections, slew rate, and classification probabilities are the factors related to the UAV's sensor(s). The factor, time step in refueling state is used to determine how many time steps a UAV is going to spend in their refueling state and how long it will be unavailable. The number of UAVs and other controllable factors provide a better understanding of the results. How does the number of UAVs affect overall performance? Does one UAV with slower speed perform better than multiple UAVs with higher speeds? Which configuration of UAV provides the best outcome over the alternatives analyzed?

2. Robust Design

Robust design is a method pioneered by Dr. Genichi Taguchi and has been broadly used to improve engineering productivity [36]. Robust design focuses on uncontrollable sources of variation, which may exist in the system or the environment, as well as mean performance of the system. In traditional experimental design, the impact of uncontrollable factors on the response is often assumed to be constant during the experimental runs. But, this approach forms a restriction on real world decision making processes. A robust design optimizes the controllable factors in the presence of uncontrollable factors or noise factors. [37] Therefore, the resulting system works well across the noise factors that are included in the experimental design [38].

3. Uncontrollable Factors

In addition to factors that are related to UAVs and directly investigable, there are also uncontrollable factors in the experimental design. Uncontrollable factors, also known as noise factors, are factors that are hard to regulate. Yet, they may have significant effects on the response. Enemy capabilities are a typical example of the uncontrollable factors. The list of factors associated with Scouts, Red Teams, and Civilians, which are given in Table 2, constitutes the uncontrollable factors for this study. Red Agents have a perfect stealth value in Enemy Contact 3 state. So, all the factors in this part affect their ability to avoid detection.

B. NEARLY ORTHOGONAL LATIN HYPERCUBE (NOLH) DESIGNS

The Nearly Orthogonal Latin Hypercube (NOLH) design developed by Cioppa (2002) is used in this study [39]. A NOLH design is a special case of Latin Hypercube (LH) designs. The experimental region in a NOLH design is shaped by the minimum and maximum levels of each factor. It is impossible to run a model for all possible combinations of factor levels, even with today's supercomputers. If there are many factors to vary in the design, we need advanced techniques to analyze the effects of these factors simultaneously. Therefore, a NOLH design is chosen to efficiently provide information from the experimental runs for the 21 factors in this study.

The Excel spreadsheet, from the SEED Center for Data Farming at the Naval Postgraduate School in Monterey, was developed by Professor Susan Sanchez and is used to build the NOLH design for this study [29]. The spreadsheet allows building different designs depending on the number of factors (minimum 7, maximum 29). We use the 17–22 factors design. The spreadsheet takes the high level, low level, and decimal points as inputs and returns an equally spaced permutation of values in between defined levels for each factor. Figure 19 depicts the first 10 rows of the NOLH design for the 21 factors varied in this study.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1	low level	9	6	2	1	1	1	0.1	0.05	1	1	3	6	4	6	5	3	2	6	1	6	0
2	high level	45	30	5	4	10	10	0.8	0.33	12	8	24	24	18	30	50	12	30	12	10	18	1
3	deci-mals	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0
4	factor name	UAVSpeed_Default	UAVSpeed_EnContact	UAVHeight_Default	UAVHeight_ENContact	UAVMaxClassRange_Default	UAVMaxClassRange_EnContact	UAVPClassAtMaxRange_Default	UAVPClassAtMaxRange_ENConatact	UAVTimeBtwDetMax_Default	UAVTimeBtwDetMax_EnContact	UAVFuelLevel	UAVTimeStepInRefueling	SlewRate InEnConState	Scout_SensorRange	Scout_ComRangeWithRed	Scout_ComLatencyWithRed	Red_SensorRange	Red_IntraSquadComDelays	Civilian_ComRangeWithRed	Civilian_ComLatencyWithRed	Civilian_ComExist
5		180	170	3000	2000	4000	4000	0.21	0.26	105	120	17100	1200	60	3000	4700	18	2600	9	9000	36	0
6		410	130	3000	2000	2000	2000	0.09	0.11	90	60	19800	1020	65	2900	3800	20	2700	9	6000	30	0
7		250	240	2000	2000	5000	5000	0.18	0.23	120	75	11700	540	55	2700	5000	18	1800	7	9000	28	0
8		340	270	3000	2000	5000	5000	0.13	0.16	60	60	10800	780	45	3000	3500	24	1900	8	6000	30	0
9		90	150	4000	2000	2000	2000	0.25	0.31	180	75	4500	1440	80	1200	2500	14	2700	10	8000	28	0
10		340	160	4000	1000	5000	5000	0.05	0.06	60	30	6300	1440	65	1800	1900	12	2800	11	8000	30	0
11		230	300	4000	2000	2000	2000	0.25	0.31	180	90	16200	480	20	900	2600	12	2800	8	9000	28	0
12		300	230	5000	1000	4000	4000	0.04	0.05	60	30	11700	480	30	1300	2000	14	1500	7	10000	26	0
13		100	70	3000	2000	3000	3000	0.14	0.17	135	105	17100	660	60	1200	4800	20	2400	12	4000	12	1
14		440	80	3000	2000	2000	2000	0.16	0.2	45	30	11700	480	70	900	4600	14	2200	10	3000	20	1

Figure 19. NOLH design spreadsheet for 17–22 factors design from Tom Cioppa’s 2002 Ph.D. dissertation.

1. Space-filling Property of NOLH Design

The NOLH design has good space-filling filling properties [40]. Space-filling means the design points (DPs) are scattered uniformly across the possible range of input data. The scatter plot matrix is one of the primary graphical tools used to visualize relationships between variables. Scatter plot matrices for controllable and uncontrollable factors are shown in Figure 20 and Figure 21, respectively. (Scatterplot matrix for all factors is included in Appendix B.) The entries in the matrix are the pairwise comparisons of the factors in the experimental design. For example, the first scatter plot of Figure 20, in row 1, column 1, contains the input settings between UAV speed in enemy contact state and UAV speed in default state. The coverage of factor levels for both plots verifies the broad space-filling of our NOLH design.

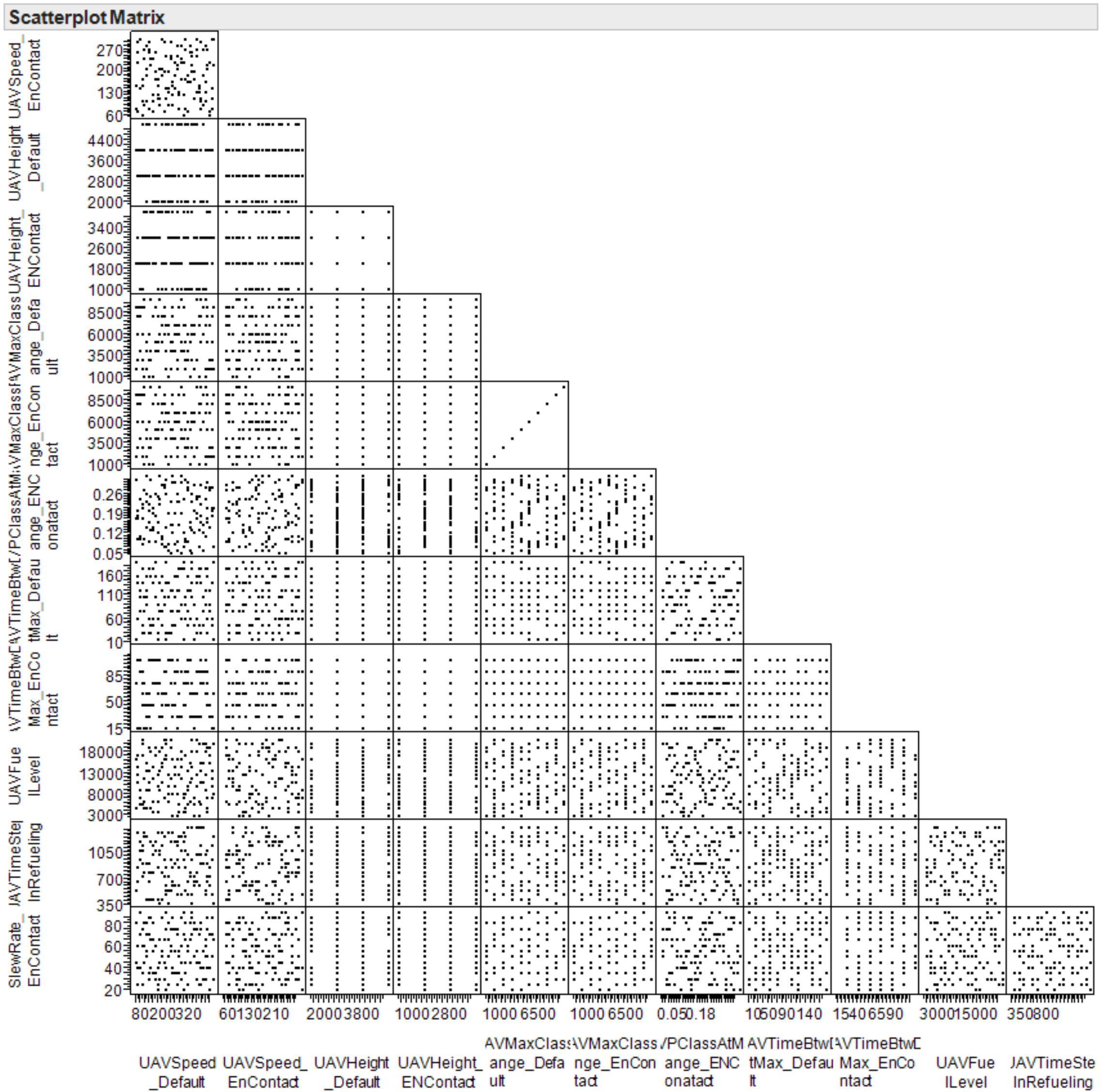


Figure 20. Scatterplot matrix for controllable factors.

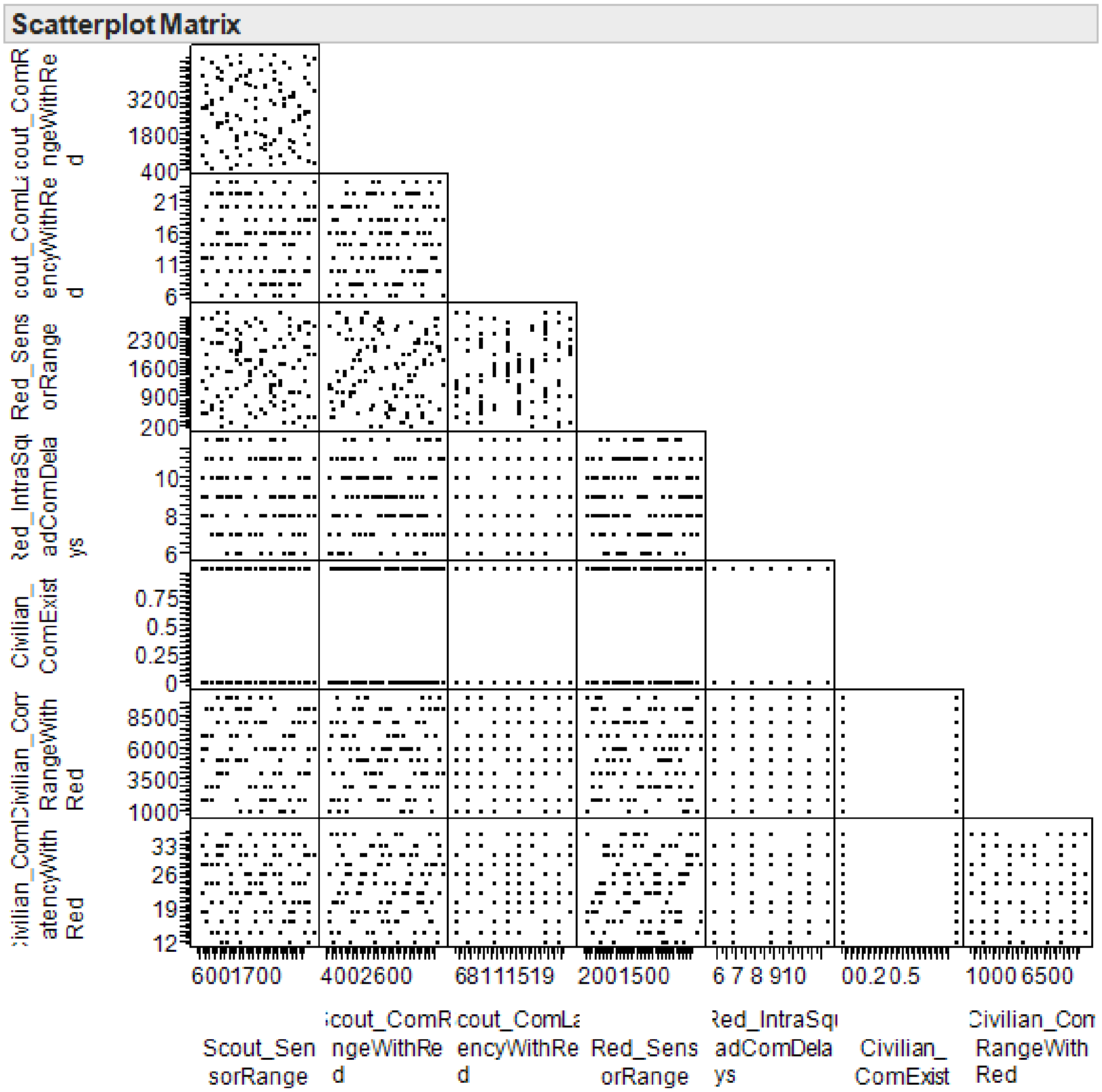


Figure 21. Scatterplot matrix for uncontrollable factors.

2. Near Orthogonality of NOLH Design

In addition to the space filling property, orthogonality is also desirable in a design because it renders uncorrelated estimates for the regression coefficients. The correlation diagram represented in Figure 22 confirms that the correlations between the factors in the experiment are insignificant. A value of 1, colored red, implies a very strong positive correlation, while a value of -1, colored blue, represents a very strong negative correlation. The diagonal of the diagram displays the correlation of a factor by itself.

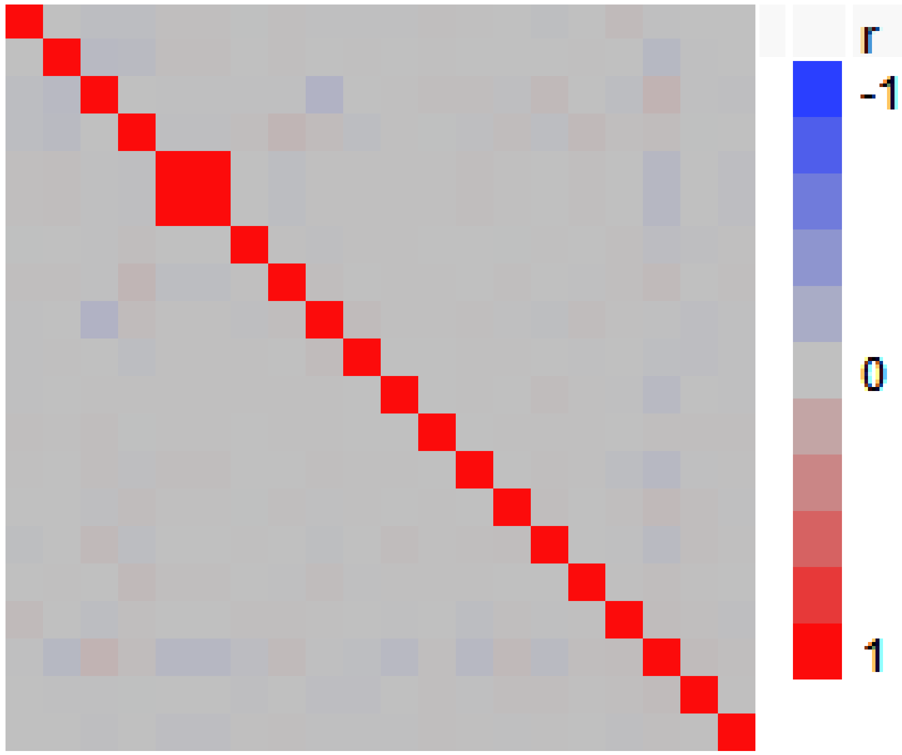
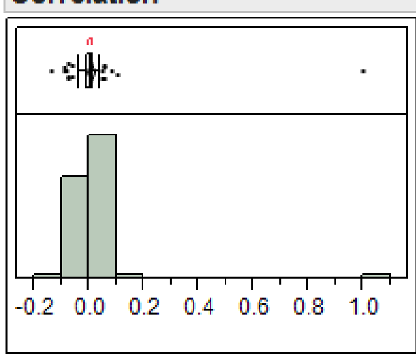


Figure 22. Correlation diagram for all of the factors in the experiment.

The histogram of correlations, among all factors, given in Figure 23 displays that the mean correlation is 0.004. The results of the correlation diagram and the histogram verify that our design is nearly orthogonal.

Distributions

Correlation



Quantiles

100.0%	maximum	1
99.5%		1
97.5%		0.05275
90.0%		0.0268
75.0%	quartile	0.01225
50.0%	median	0.0033
25.0%	quartile	-0.0091
10.0%		-0.0315
2.5%		-0.0797
0.5%		-0.1377
0.0%	minimum	-0.1377

Summary Statistics

Mean	0.0049767
Std Dev	0.0776412
Std Err Mean	0.0056327
Upper 95% Mean	0.0160878
Lower 95% Mean	-0.006134
N	190

Figure 23. Histogram of correlation between all of the factors in the experiment.

C. MODEL RUNS

1. Tools and Techniques

Sanchez's NOLH design spreadsheet provides 129 DPs for 21 factors varied in the design. After using the design sheet, we add another 13 dependent input variables to the design. The whole design is then crossed with the number of UAVs (1 up to 4) in Excel. The final design we create contains 516 DPs.

The software package Xstudy, written by SEED Center Research Associate Steve Upton, is used to create the mapping between variables in the design and elements of the MANA scenario file, and to specify the number of independent replications per DP. Consequently, a design file in xml format is generated. The XStudy software package is available at http://harvest.nps.edu. A follow on to XStudy is software called OldMcData, which is also written by Steve Upton, it manages the generation of scenario files for each design point using the experimental design sheet, the baseline MANA xml files created for each scenario, and the XStudy xml files. The OldMcData software package is also available at http://harvest.nps.edu.

The open source software package Condor, which is available from the University of Wisconsin at http://www.cs.wisc.edu/condor/, distributes and manages the jobs across a set of available processors. In our study, the model is run on cluster, called "reaper," with 44 processors. Finally, a postprocessor included in OldMcData is used to combine all of the simulation outputs, with their corresponding input values, into a single comma-separated (csv) file.

2. Time Analysis

The run time for a single replication of the base case is about 7 to 8 minutes on average. The number of replications desired is calculated using the formula in equation 1. We use an α value of 0.05 and β value of 0.10. Therefore, we need to take about 200 samples in order to have a 90% chance of detecting a difference in means of 1 for a test with a 5% type-I error rate. As a result, 200 replications are made for each design point. Figure 24 displays the change in sample size required based on the empirical variance of mean number of Red Agents classified.

$$n = \left(\frac{\sigma(Z_\alpha + Z_\beta)}{(\mu_0 - \mu^{'})} \right)^2 \tag{1}$$

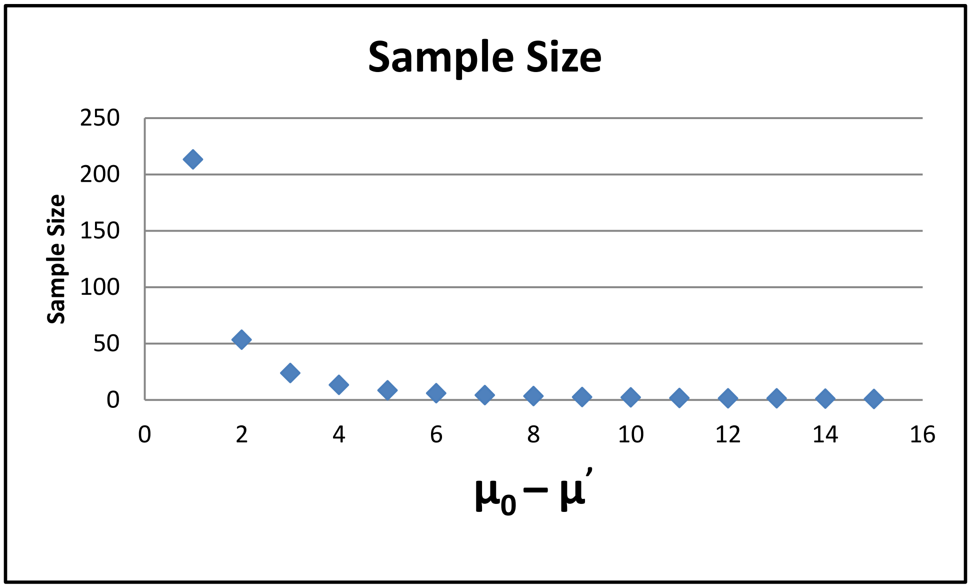


Figure 24. Number of replications required per design point.

We end up with a total of 103,200 simulated terrorist incursions, which would have taken about 573 days to run using only a single processor. However, since the model is run on a cluster with 44 processors, it takes about only about 13 days to complete all of the runs. The model runs took longer time than expected due to failures on a section of node during the runs. However, this analysis would require approximately 35×10^{11} replications with a traditional, brute-force full-factorial design. Graphical comparisons for the required number of runs and time needed to complete these runs are provided in Figure 25 and Figure 26, respectively.

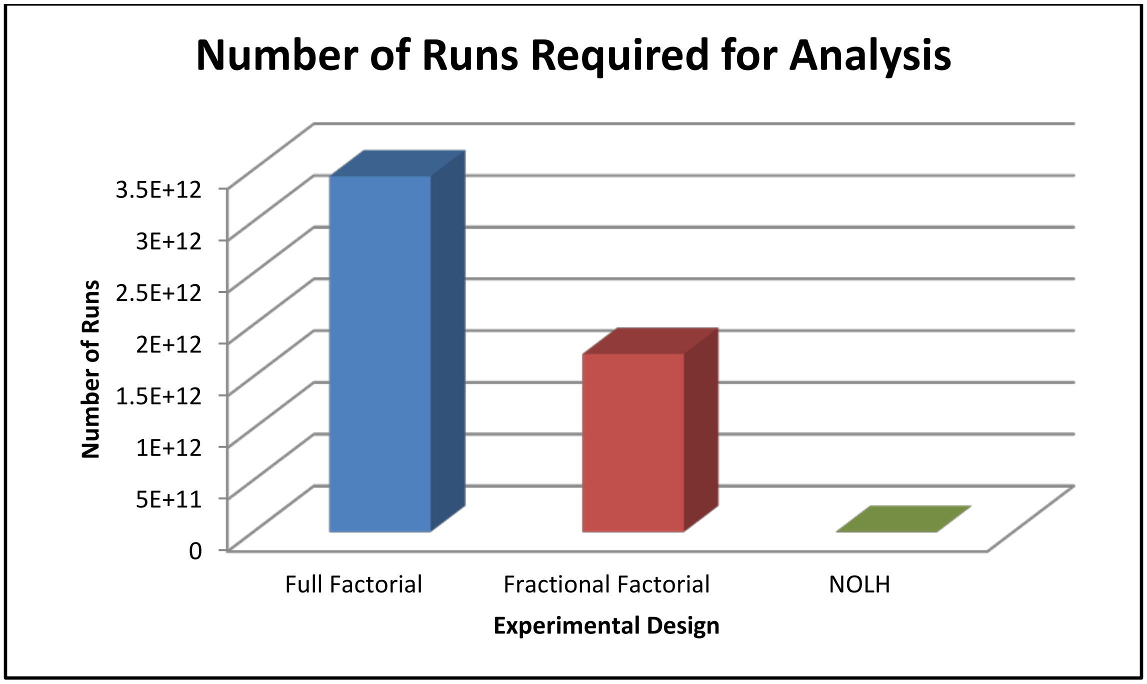


Figure 25. Graphical comparison of the number of replications required for the study with full factorial design, fractional factorial design, and NOLH design.

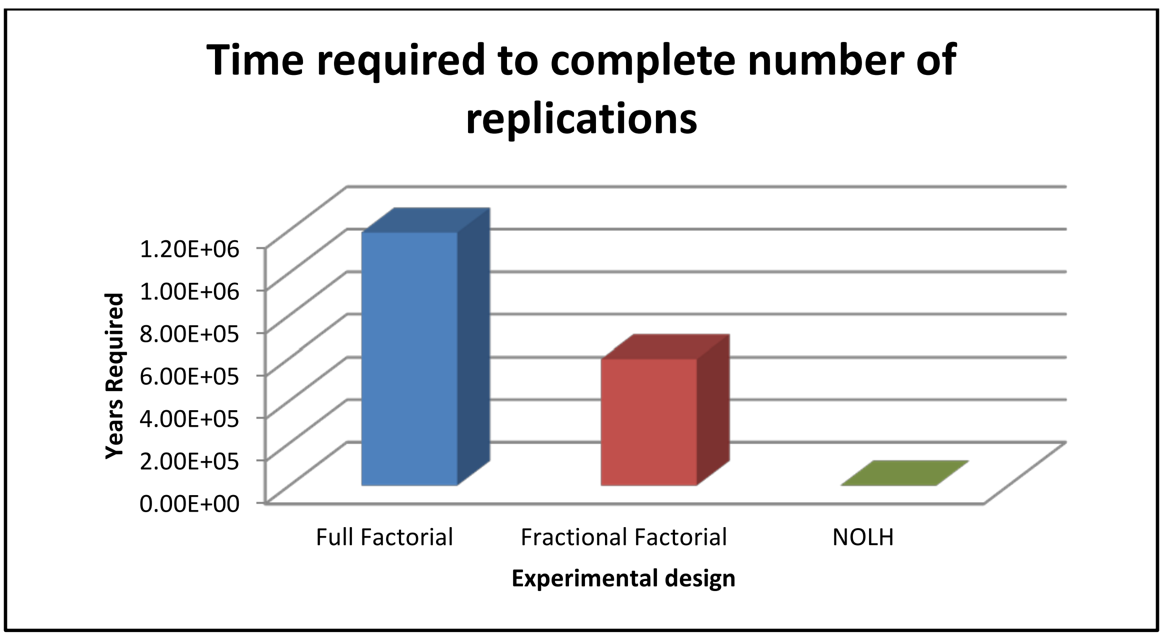


Figure 26. Graphical comparison of the years required to complete number of runs with full factorial design, fractional factorial design, and NOLH design.

V. DATA ANALYSIS

In this chapter, we provide a quick review of the analysis tools utilized in this study. Then, we discuss the results of some initial runs that were made without using an experimental design. In the last section, we present a discussion of various statistical modeling techniques to analyze the relationships between the factors in the experimental design and our MOEs.

A. ANALYSIS TOOLS

1. JMP

JMP, one of the two tools used to analyze the data, was created by SAS in 1986 as a data exploration tool. According to JMP's official website, available at http://www.jmp.com, it provides graphical and visual interpretations of data [41]. Additionally, JMP has a dynamic user interface that allows users to conduct interactive data analysis.

JMP enables a wide variety of statistical techniques, such as linear regression, nonlinear regression, partition trees, time series analysis, Gaussian process, neural networks, and more. We use JMP Statistical Discovery Software version 10.0.0 to perform the regression analysis for this study.

2. R

R is a language and environment for data manipulation, statistical computing, and graphical display. It was developed by John Chambers and his colleagues based on the code written for the S language and its environment [42]. R is free software available in source code format and capable of working on various platforms, such as Windows, UNIX, and MacOS. Users can extend R's functionality by adding new functions or installing new packages. In addition to JMP, we use R as a supplementary tool for our analysis.

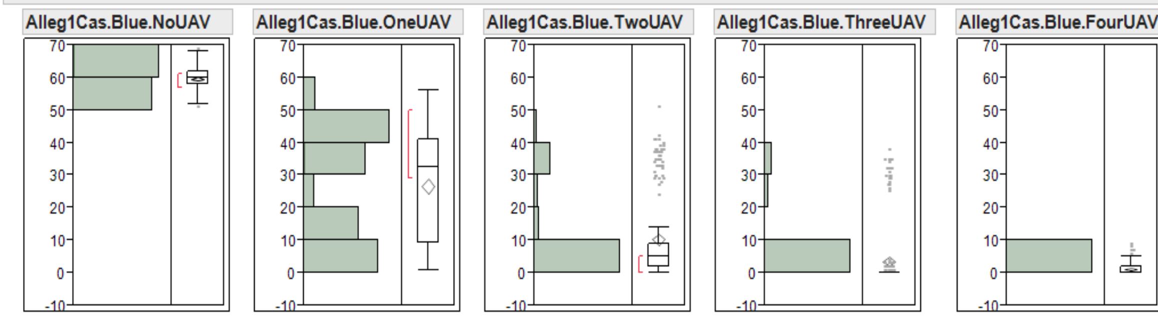
B. RESULTS OF INITIAL RUNS

Following the creation of the model in MANA, 200 initial runs are made for the base case for each scenario. We expect to see how results change depending on the number of UAVs through these preliminary runs and get information on the variability associated with the numerous random elements in the model.

1. Total Number of Red Agents Arrived at Destination

There are 150 Red Agents that are trying to cross the border in the simulation model. They can either be detected and classified by Blue Agents, or they can reach their destination without being detected. Upon reaching its goal undetected, each Red Agent kills one Blue Target which is placed at the destination of Red Agents. Thus, the number of killed Blue Targets forms a surrogate for the number of Red Agents that reach the destination. Figure 27 displays the distribution of the number of Red Agents that reach the destination for the scenarios analyzed. The histogram provides the distribution of arrived Red Agents within the predefined time frame. In addition to the histogram, box plots depict the summary statistics of the data pictorially. According to the summary statistics, on average, 60 of the Red Agents are able to reach their destination within the predefined maximum timeline. The mean number of arrived Red Agents decreases with the number of UAVs (0 up to 4). The mean number of arrived Red Agents drops to 1.21 for scenario five with four UAVs.

Distributions



Quantiles

		Alleg1Cas.Blue.NoUAV	Alleg1Cas.Blue.OneUAV	Alleg1Cas.Blue.TwoUAV	Alleg1Cas.Blue.ThreeUAV	Alleg1Cas.Blue.FourUAV
100.0%	maximum	69	56	51	38	9
99.5%		68.995	55.985	50.955	37.985	8.995
97.5%		67	51.975	40.975	34.975	6.975
90.0%		64	45.9	35	26.9	3
75.0%	quartile	62	41	9	0	2
50.0%	median	60	32.5	5	0	0
25.0%	quartile	58	9.25	2	0	0
10.0%		55	5	0	0	0
2.5%		53	3	0	0	0
0.5%		51.005	1.005	0	0	0
0.0%	minimum	51	1	0	0	0

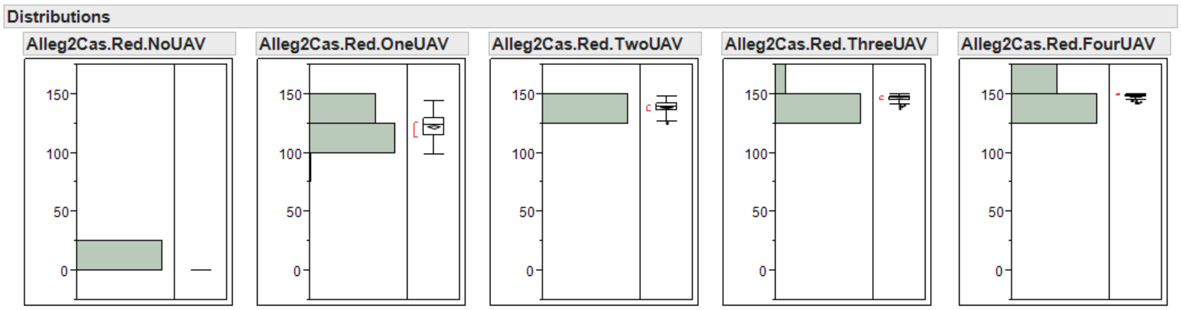
Summary Statistics

	Alleg1Cas.Blue.NoUAV	Alleg1Cas.Blue.OneUAV	Alleg1Cas.Blue.TwoUAV	Alleg1Cas.Blue.ThreeUAV	Alleg1Cas.Blue.FourUAV
Mean	59.695	26.645	10.37	3.615	1.21
Std Dev	3.5883641	16.369139	12.989486	9.7065887	1.7235875
Std Err Mean	0.2537357	1.1574729	0.9184953	0.6863595	0.121876
Upper 95% Mean	60.195356	28.927486	12.181233	4.968471	1.4503343
Lower 95% Mean	59.194644	24.362514	8.5587671	2.261529	0.9696657
N	200	200	200	200	200

Figure 27. Distribution of total number of Red Agents that reach the destination.

2. Total Number of Classified Red Agents

The Red Agents in the simulation model can only be classified by the UAVs. The Red Agents are the most valuable targets. Therefore, they have the highest priority in the UAV sensor set up. Following their classification, Red Agents are devolved to the Blue Killing Agent to prevent multiple classifications. The distribution of the number of classified Red Agents is provided in Figure 28. The number of classified Red Agents is 0, as expected, when there are no UAVs over the region. The mean number of classified Red Agents increases with the number of UAVs. The mean of the total number of classified Red Agents jumps from 0 to 122.485 for scenario two with one UAV. The total number of classified Red Agents can reach 150 for scenario three and scenario four.



Quantiles

		NoUAV	OneUAV	TwoUAV	ThreeUAV	FourUAV
100.0%	maximum	0	144	148	150	150
99.5%		0	143.99	147.995	150	150
97.5%		0	139	146	150	150
90.0%		0	134	144	150	150
75.0%	quartile	0	130	142	148	150
50.0%	median	0	123.5	139	147	149
25.0%	quartile	0	115.25	136	145	148
10.0%		0	111.1	133.1	142	146
2.5%		0	102.05	130	140	143.025
0.5%		0	99.005	125.005	137.01	142
0.0%	minimum	0	99	125	137	142

Summary Statistics

	NoUAV	OneUAV	TwoUAV	ThreeUAV	FourUAV
Mean	0	122.485	138.835	146.24	148.355
Std Dev	0	9.1563623	4.2186205	2.6604114	1.7958565
Std Err Mean	0	0.6474526	0.2983015	0.1881195	0.1269862
Upper 95% Mean	0	123.76175	139.42324	146.61096	148.60541
Lower 95% Mean	0	121.20825	138.24676	145.86904	148.10459
N	200	200	200	200	200

Figure 28. Distribution of total number of classified Red Agents.

The average number of classified Red Agents is plausibly high even with two UAVs over the area of interest. Nevertheless, the variability decreases when we increase the number of UAVs. Figure 29 and Figure 30 provide the average and standard deviation of the number of arrived and classified Red Agents for the results of 200 initial runs in each scenario. As a result of the intuition gained through the initial runs, the design is crossed for the number of UAVs (1 up to 4).

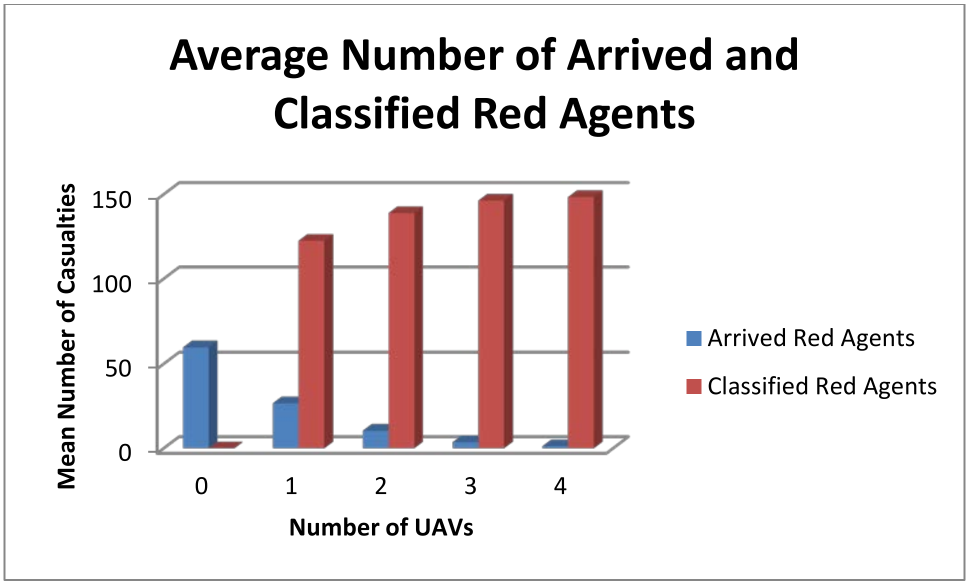


Figure 29. Average number of arrived and classified Red Agents based on the results of 200 initial runs.

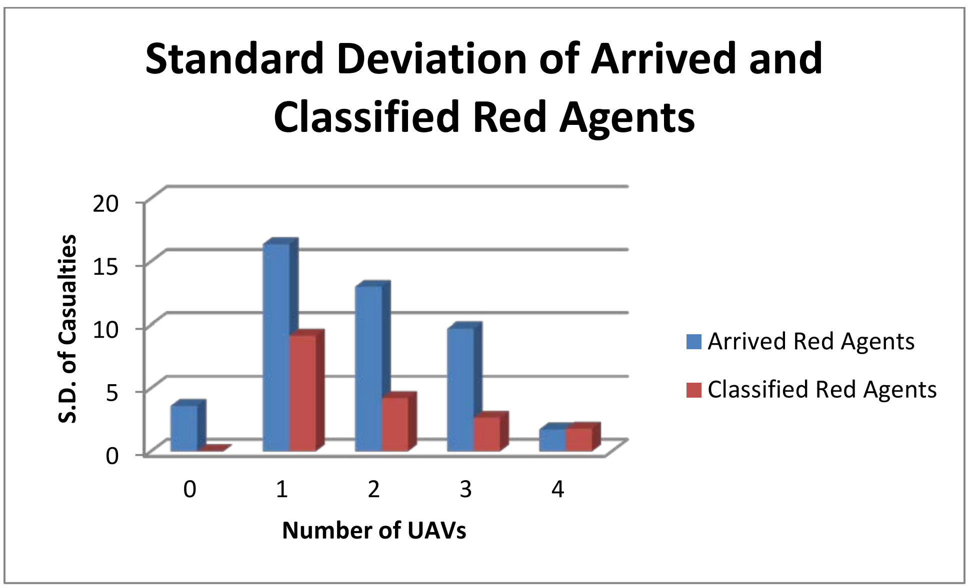


Figure 30. Standard deviation of arrived and classified Red Agents based on the results of 200 initial runs.

C. RESULTS OF RUNS FOR CROSSED DESIGN

We use the mean of 200 replications as our measure of effectiveness (MOEs). As a result, we reduce the number of data points from 103,200 to 516. This facilitates visual displays of the data.

1. Measure of Effectiveness

The purpose of the study is to analyze the effectiveness of UAVs on detection of terrorists over a hard topographical region. Therefore, we describe two MOEs to measure the effect of model factors on UAV performance. The mean numbers of arrived and classified Red Agents are the two MOEs investigated for the purpose of this analysis. An initial assessment of the MOEs highlighted that there is a strong negative correlation between the numbers of arrived and classified Red Agents. Figure 31 shows the correlation between these two MOEs. The correlation between the MOEs is -0.6898.

Multivariate

Correlations

	Mean(#of_Arrived_RedAgents)	Mean(#of_Classified_RedAgent)
Mean(#of_Arrived_RedAgents)	1.0000	-0.6898
Mean(#of_Classified_RedAgent)	-0.6898	1.0000

Scatterplot Matrix

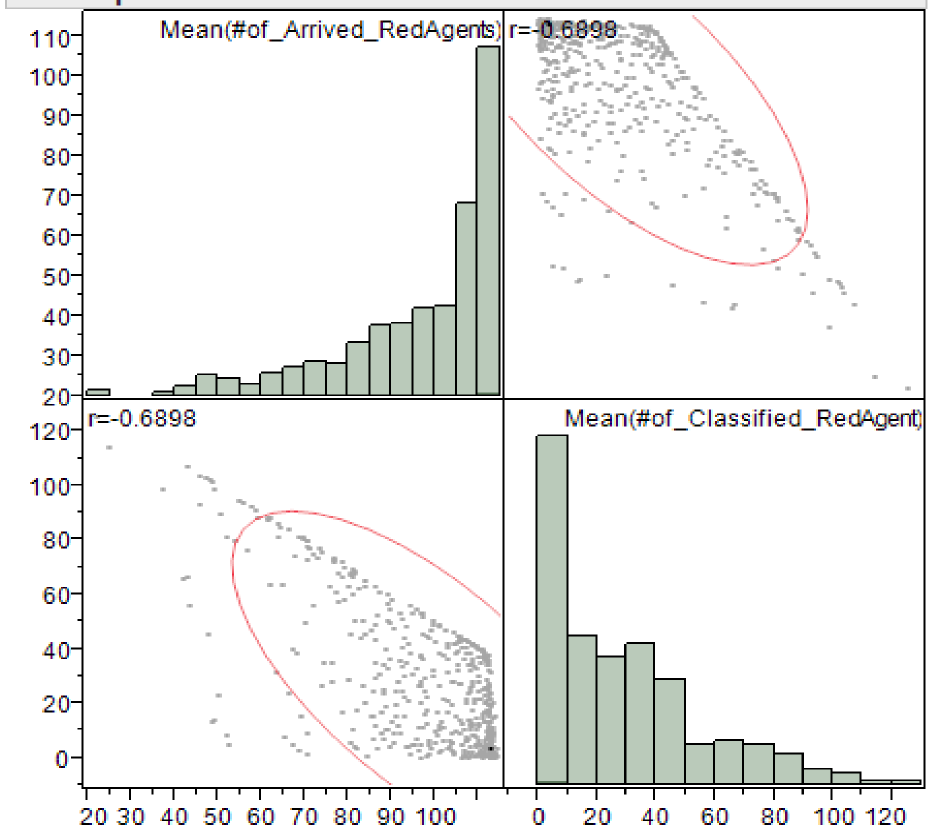


Figure 31. Scatterplot of the mean numbers of arrived and classified Red Agents.

Since the two MOEs are so highly correlated, we choose the number of classified Red Agents as the primary MOE to study the effect of factors on the UAV's performance. The color map of correlations, ranging from -1 to 1 and provided in Figure 32, shows that the two MOEs have a strong negative relationship. Consequently, we expect independent regressors to have reverse impacts on these two MOEs.

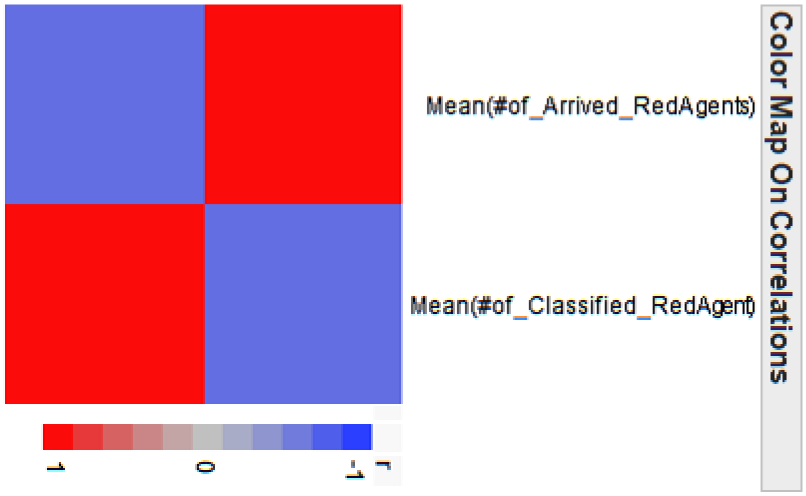


Figure 32. Color map of correlations among MOEs.

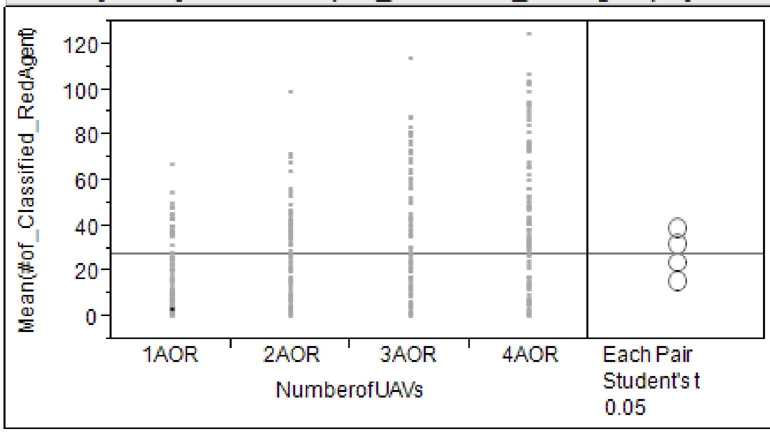
2. T-test for Comparison of the Sample Mean

The scenarios developed for the different number of UAVs are compared with each other, in terms of mean number of classified Red Agents, to explore how different number of UAVs contributes to detection and classification of Red Agents.

The results of the T-Test for the mean number of classified Red Agents yield that there is a statistically significant difference between the scenarios at a 95% confidence level (or when α = .005). As expected, the mean number of classified Red Agents increases with the number of UAVs as shown in Figure 33. A detailed comparison report of each pair is provided in Appendix C.

In addition to the T-test, we look at the trend between number of UAVs and corresponding coefficient estimates, and verify the linear relationship. Then, we fit two distinct models changing the classification of number of UAVs as continuous and as discrete. The F-test critical value, calculated based on these two models is 0.47, which is much less than the F-statistic critical value of 2.19 [43]. Hence, we fail to reject the null hypothesis and conclude that it is okay to treat the number of UAVs as a continuous variable. As a result, we conduct the rest of the analysis using the number of UAVs as a continuous variable.

Oneway Analysis of Mean(#of_Classified_RedAgent) By NumberofUAVs



Means Comparisons

Comparisons for each pair using Student's t

Ordered Differences Report

Level	- Level	Difference	Std Err Dif	Lower CL	Upper CL	p-Value
4AOR	1AOR	23.12419	3.029404	17.17259	29.07578	<.0001*
3AOR	1AOR	16.46512	3.029404	10.51352	22.41671	<.0001*
4AOR	2AOR	14.82438	3.029404	8.87279	20.77597	<.0001*
2AOR	1AOR	8.29981	3.029404	2.34821	14.25140	0.0064*
3AOR	2AOR	8.16531	3.029404	2.21372	14.11690	0.0073*
4AOR	3AOR	6.65907	3.029404	0.70748	12.61066	0.0284*

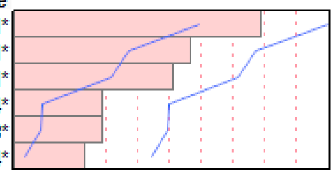


Figure 33. T-test for comparison of mean number of classified Red Agents.

3. Linear Regression

We use linear regression to explore the relationship between the response variable and the input factors. The linear model presumes that the regression function is linear or that the linear model is an acceptable approximation [44]. The basic mathematical interpretation of the linear model is stated by the following equation [44] :

$$f(X) = \left(\beta_0 + \sum_{j=1}^{p} X_j \beta_j \right) \tag{2}$$

In the equation, X_j represents the independent regressors. The factors presented in Table 2 are the independent regressors of our study. β_0 represents the intercept and β_j stands for the coefficients of the independent regressors. In our study, we want to fit the number of classified Red Agents using the regression function on the factors.

a. The Basic Model

The mean number of classified Red Agents is used as the response variable to conduct a stepwise linear regression [44] with all of the independent factors in the experimental design. The resulting model has an R^2 value, the coefficient of determination, of 0.7948 and an adjusted R^2 value of 0.7903, which means that the regressors in the model explain approximately 80% of the variability in the response. We then perform model diagnostics using the residual plots shown in Figure 34.

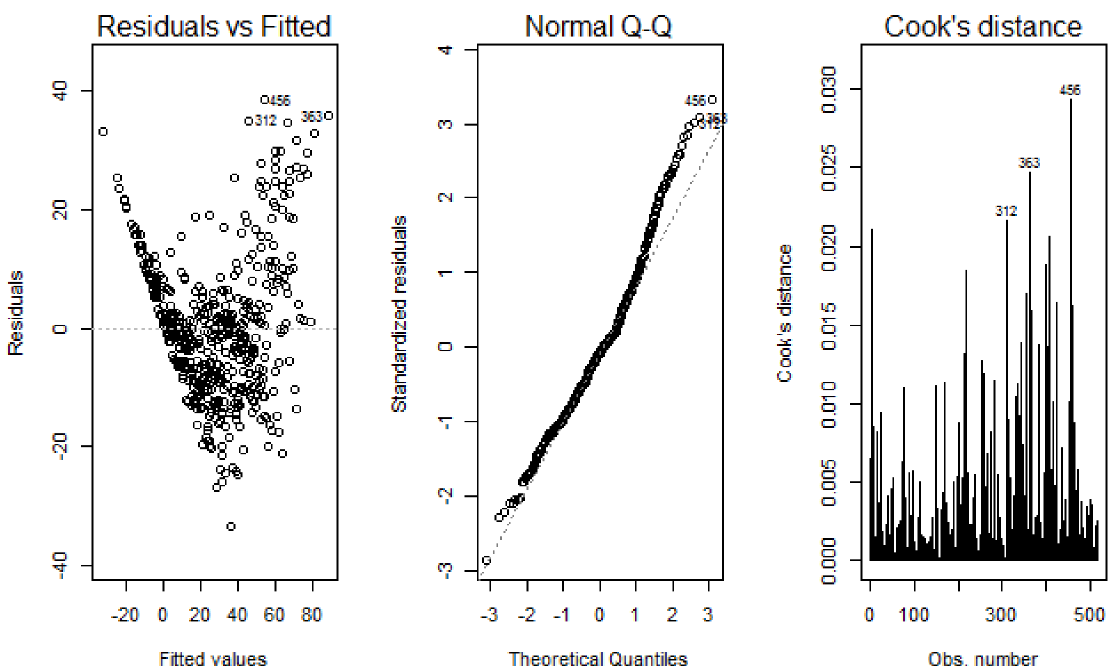


Figure 34. Residuals plots for the stepwise regression model.

All Cook's distance values are less than one, which shows that there are no influential points. However, the residual versus fitted plot indicates non constant variance in the model. Non constant variance, or heteroscedasticity, is anticipated in the simulation model due to the hard topography of the region. Additionally, the normal quantile plot points out that the errors are not normally distributed. After the diagnosis of the initial model, a Box-Cox transformation is performed on the response variable. We observe a lambda value of 0.4 through the plot provided in Figure 35 and conduct a power transformation on response.

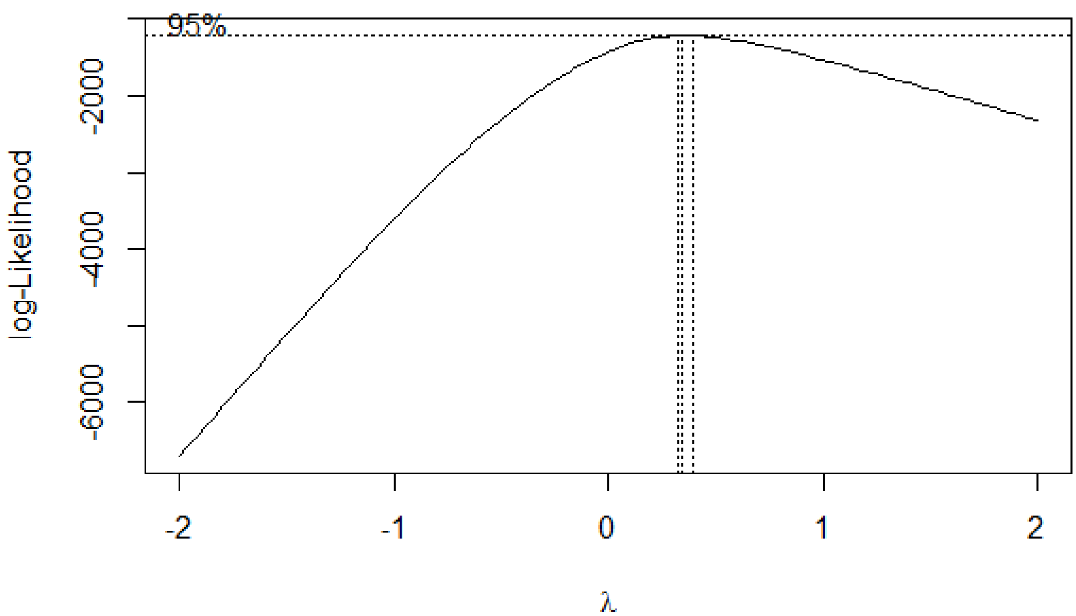


Figure 35. Graphical result of Box-Cox transformation suggests a power transformation of 0.4 on the response.

We fit a new model using the response variable with the power transformation. The heteroscedasticity and normality problems seem to be handled by this according to the plots given in Figure 36. Moreover, the R^2 value increases from 0.7923 to 0.8837. Finally, we conduct a Durbin Watson test to ensure that the autocorrelation between the regressors is zero. The test returns a Durbin Watson statistic of 2.0683 with a *p-value* of 0.7663, which is greater than our significance level of 0.05 (α = 0.05). Therefore, there is no strong evidence that violates the null hypothesis and we conclude that the autocorrelation is zero.

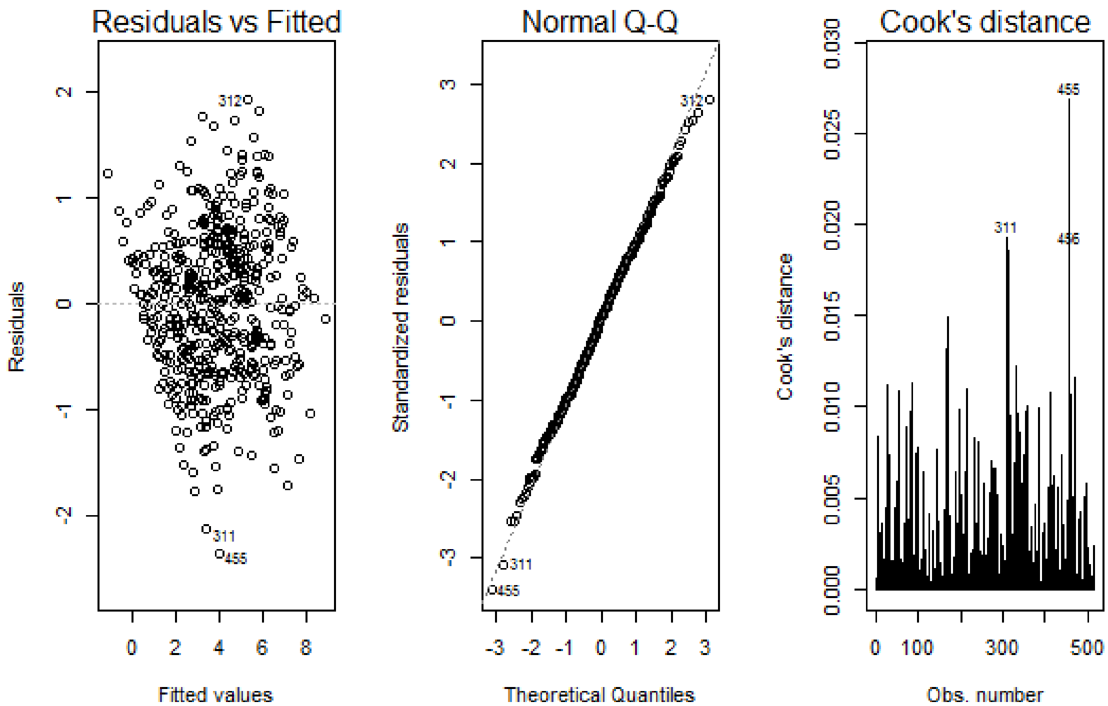
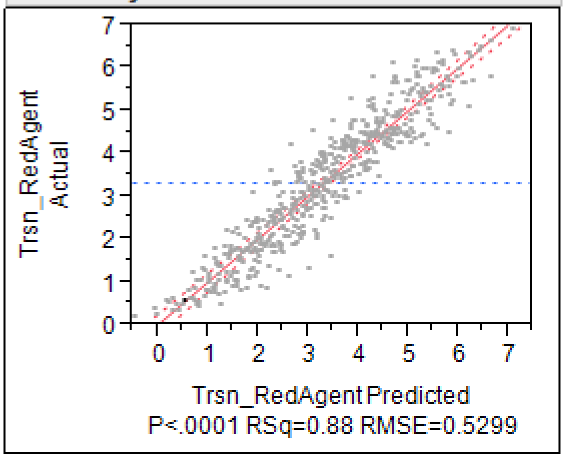


Figure 36. Residuals plot after the Box-Cox transformation on the response.

The *p-value* of the basic model is less than 0.0001, which indicates there is a highly significant relationship between the response and regressors included in the model. Figure 37 provides the summary statistics for the basic model.

Actual by Predicted Plot



Summary of Fit

RSquare	0.883724
RSquare Adj	0.881186
Root Mean Square Error	0.529927
Mean of Response	3.315134
Observations (or Sum Wgts)	516

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	11	1075.6952	97.7905	348.2292
Error	504	141.5343	0.2808	**Prob > F**
C. Total	515	1217.2295		<.0001*

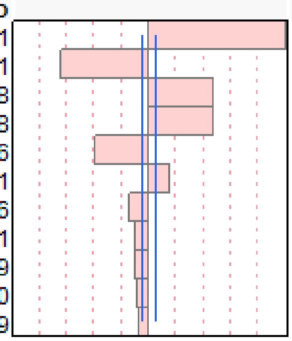
Figure 37. The statistical results for the basic model after the Box-Cox transformation.

There are 11 factors that have the highest impact on the response when $\alpha = 0.05$. Table 3 provides the list of these factors in the order of their significance level. The t-ratio changes with the contribution of the factor to the explanatory power of model. Therefore, the factors with the highest t-ratio are the most significant in the model. UAV classification range in the default state and probability of classification in the enemy contact state, Red Team sensor range, number of UAVs, time between detections, and UAV fuel level are the major factors that affect the classified number of Red Agents within the predefined time frame.

Table 3. Sorted parameter estimates for the basic model

Sorted Parameter Estimates

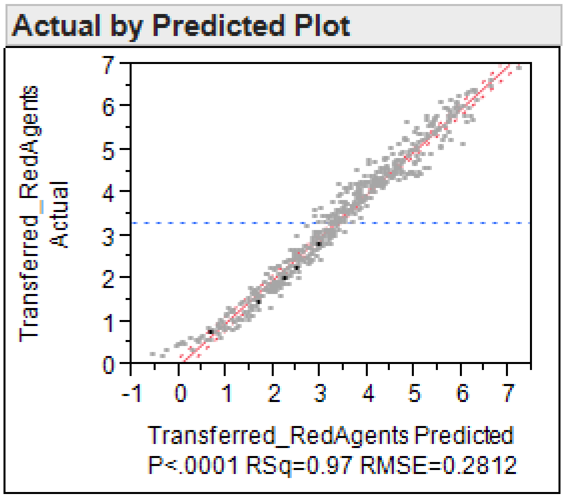
Term	Estimate	Std Error	t Ratio	Prob>|t|
UAVMaxClassRange_Default	0.0003713	8.816e-6	42.11	<.0001*
Red_SensorRange	-0.000776	2.864e-5	-27.11	<.0001*
UAVPClassAtMaxRange_EnContact	5.7812371	0.286438	20.18	<.0001*
NumberofUAVs	0.4190199	0.020866	20.08	<.0001*
UAVTimeBtwDetMax_Default	-0.007962	0.000484	-16.46	<.0001*
UAVFuelLevel	2.8363e-5	4.225e-6	6.71	<.0001*
UAVTimeBtwDetMax_EnContact	-0.004233	0.000748	-5.66	<.0001*
UAVTimeStepInRefueling	-0.000328	7.44e-5	-4.41	<.0001*
Civilian_ComExist	-0.192873	0.047131	-4.09	<.0001*
UAVSpeed_Default	-0.000758	0.000223	-3.40	0.0007*
Civilian_ComRangeWithRed	-2.538e-5	8.788e-6	-2.89	0.0040*



b. The Saturated Model

Following the basic model, we fit models that include interactions and higher order terms. First, we fit a model with all pairwise interactions among the significant factors and compare this model with the basic model, without interaction effects, using an F test. The F test returns a *p-value* of 2.2e-16. As a result, we strongly reject the null hypothesis and conclude that the saturated model provides an improvement over the basic model. The model with all two way interactions has an R^2 value of 0.9334 with 30 terms included in the model. The statistical results and sorted parameter estimates for the model with interaction effects are shown in Appendix D.

Likewise, we fit a model including quadratic effects of significant factors in the model using stepwise linear regression. The results indicate that quadratic term for time between detections, UAV classification range, number of UAVs, Red Team sensor range, and UAV fuel level are significant. An improved R^2 value of 0.9684 is provided by the model with these significant interactions and quadratic terms. Figure 38 provides the statistical summary of the resulting model with 28 terms contributing to the explanatory power of the model.



Summary of Fit

RSquare	0.968363
RSquare Adj	0.966544
Root Mean Square Error	0.281205
Mean of Response	3.315134
Observations (or Sum Wgts)	516

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	28	1178.7195	42.0971	532.3627
Error	487	38.5100	0.0791	Prob > F
C. Total	515	1217.2295		<.0001*

Figure 38. Statistical results for the model with interactions and quadratic terms.

Finally, we observe the change in the R^2 value of the model by adding parameters to the model in their order of their significance. The purpose is to reduce the complexity without significantly demoting the predictive capability of the model. That is, we desire a parsimonious model. According to the plot in Figure 39, the R^2 value almost evens out after the seventeenth parameter. This indicates that only 17 of the 28 parameters in the model with main effects, interactions, and quadratic effects contribute the vast majority of the predictive power of the model.

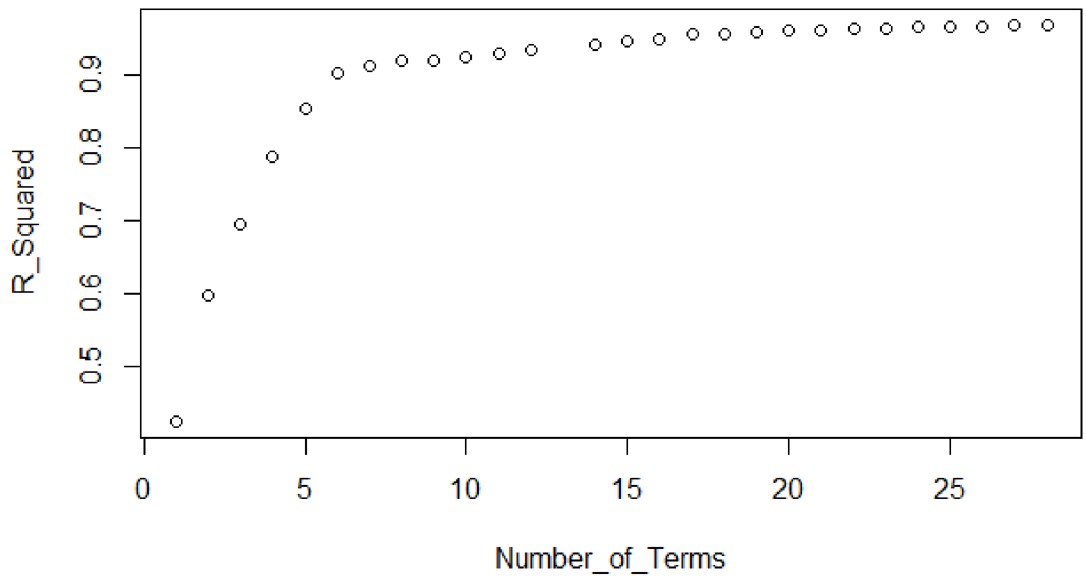


Figure 39. R^2 value plot for the number of parameters included in the model in the order of their significance.

The reduced size model, which has an R^2 value of 0.957048, includes the factors listed in Table 4. We see that UAV classification range in default state and probability of classification in enemy contact state, Red sensor range, number of UAVs, time between detections in the default state, and quadratic effects of classification range have the highest impact on the model.

Table 4. Sorted parameter estimates for the reduced-size model highlighted by the R^2 method given in Figure 39.

Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
UAVMaxClassRange_Default	0.0003707	4.679e-6	79.23	<.0001*
Red_SensorRange	-0.000776	1.52e-5	-51.06	<.0001*
UAVPClassAtMaxRange_EnContact	5.7743572	0.152	37.99	<.0001*
NumberofUAVs	0.4190199	0.011072	37.84	<.0001*
UAVTimeBtwDetMax_Default	-0.007969	0.000257	-31.05	<.0001*
(UAVMaxClassRange_Default-5503.88)*(UAVMaxClassRange_Default-5503.88)	-5.836e-8	1.981e-9	-29.45	<.0001*
UAVFuelLevel	2.8437e-5	2.242e-6	12.68	<.0001*
UAVTimeBtwDetMax_EnContact	-0.004274	0.000397	-10.77	<.0001*
(UAVMaxClassRange_Default-5503.88)*(UAVPClassAtMaxRange_EnContact-0.19016)	0.0006061	6.681e-5	9.07	<.0001*
(UAVPClassAtMaxRange_EnContact-0.19016)*(UAVPClassAtMaxRange_EnContact-0.19016)	-18.52073	2.150739	-8.61	<.0001*
UAVTimeStepInRefueling	-0.000331	3.948e-5	-8.38	<.0001*
Civilian_ComExist	-0.197767	0.025014	-7.91	<.0001*
(Red_SensorRange-1601.55)*(Civilian_ComRangeWithRed-5503.88)	4.6563e-8	6.016e-9	7.74	<.0001*
(NumberofUAVs-2.5)*(UAVMaxClassRange_Default-5503.88)	0.0000319	4.167e-6	7.66	<.0001*
UAVSpeed_Default	-0.000755	0.000118	-6.39	<.0001*
(UAVTimeBtwDetMax_Default-97.5581)*(UAVTimeBtwDetMax_Default-97.5581)	4.2628e-5	6.818e-6	6.25	<.0001*
(Red_SensorRange-1601.55)*(Red_SensorRange-1601.55)	1.4424e-7	2.532e-8	5.70	<.0001*

4. Lasso Regression

The least absolute shrinkage and selection operator (lasso) is a method for estimation in linear models. It drops some coefficients off and sets the others to 0, thus attempting to return a less complex model [45]. The lasso method uses a diamond shaped constraint region and performs L1 shrinkage. The sum of squares is calculated based on various coefficients that are drawn as red contour lines in Figure 40. If the sum of squares hits one of the corners of blue diamond, then corresponding coefficients are set to 0 [46]. The amount of shrinkage in the model is driven by a tuning parameter lambda.

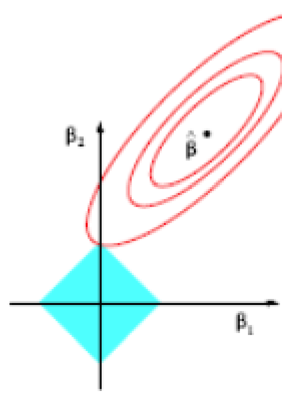


Figure 40. Estimation picture for the lasso regression where ellipses are the contours of the least squares error function and blue area is the constraint region. (From: onlinecourses.science.psu.edu).

We apply this method to the saturated model with 28 terms. Figure 41 displays the cross-validated Mean Square Error (MSE) plot. The dashed line in the plot represents the lambda value with minimal MSE plus one standard deviation. As lambda increases, MSE also increases rapidly. This means that the coefficients are reduced too much and the resulting model has a poor explanatory power. As lambda decreases, a smaller number of coefficients are set to 0.

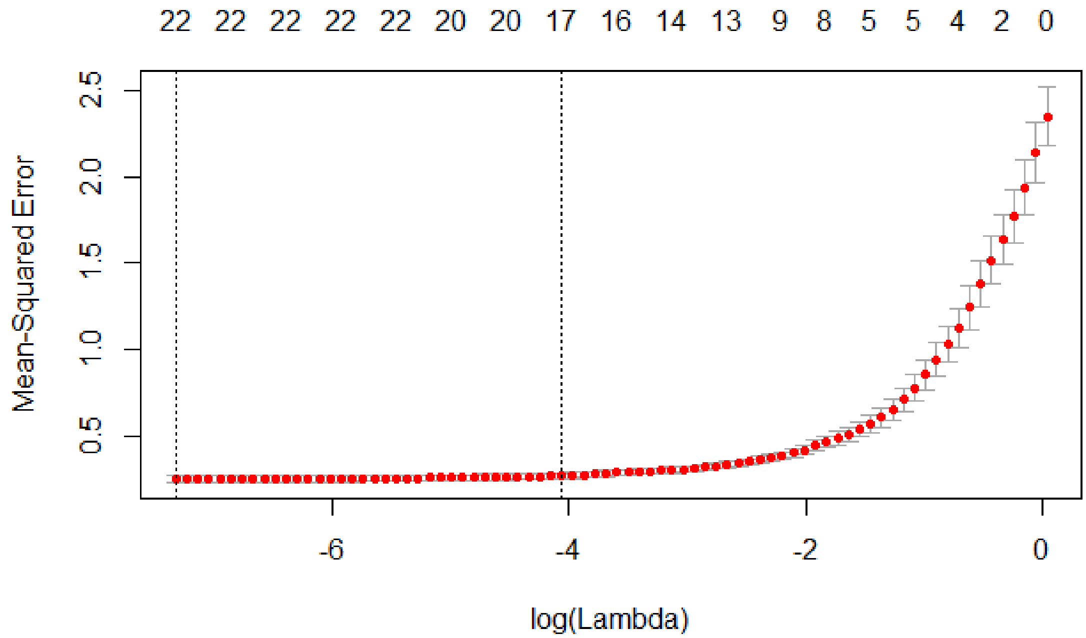


Figure 41. The cross-validated Mean Square Error.

Then, we choose the least complex model using the "one-standard-error" rule. The trace plot of coefficients is provided in Figure 42. The plot shows the nonzero coefficients in the model for different values of lambda. The dashed line in the plot represents the lambda value corresponding to minimal MSE and number of terms included in the model within one standard error. The lasso asserts 17 terms based on the minimum least squares error approach. The factors chosen by lasso regression are almost same with the factors in Table 4 except for the quadratic terms. Different than quadratic effects, lasso regression keeps civilian communication range and it's interactions with the factors time between detections and civilian communication exists.

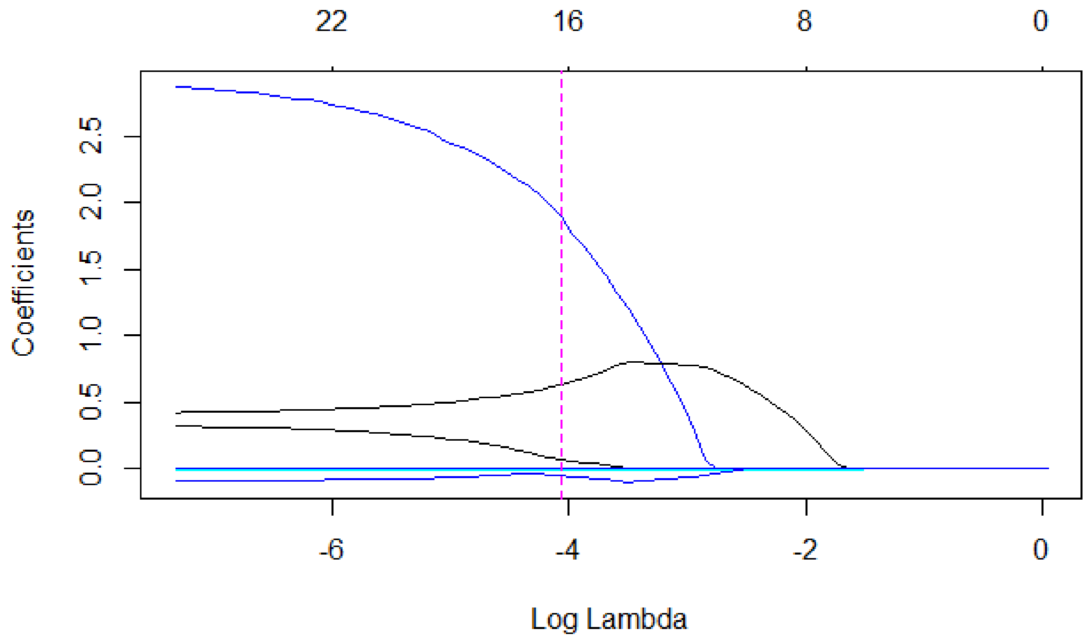


Figure 42. Trace plot of coefficients fit by lasso.

5. Regression Tree Analysis

Regression trees, also known as partition trees, provide another method to analyze regression problems. A regression tree represents the decision making steps visually and iteratively. The tree model is attained by recursively partitioning the data space and fitting a simple model based on each partition. Then, the results can be displayed as a regression tree [47]. The determination of the optimal split point is made based on the minimum sum of squares [44]. After each split, the succeeding ideal split is determined within each partition.

We build a regression tree for the mean number classified Red Agents given all input factors. When we look at the first 4 splits presented in Figure 43, we see that the results conform to the results of stepwise regression and lasso regression in previous sections. Each box in the tree structure provides the factor and level of optimal split. In addition to factor and level, the number of data points included in the split, mean number of classified Red Agents, and standard deviation within the split are also provided in the box. We see that the first split is on UAV default state classification range of 5000 meters. 200 observations have classification range less than 5000 meters with a mean response value of 11.23, whereas 316 observations have classification range greater than 5000 meters with a mean response value of 38.56. The next split occurs for Red Agent sensor range of 1400 meters. The mean number of classified Red Agents is 52.79 when the Red sensor range is less than 1400 meters.

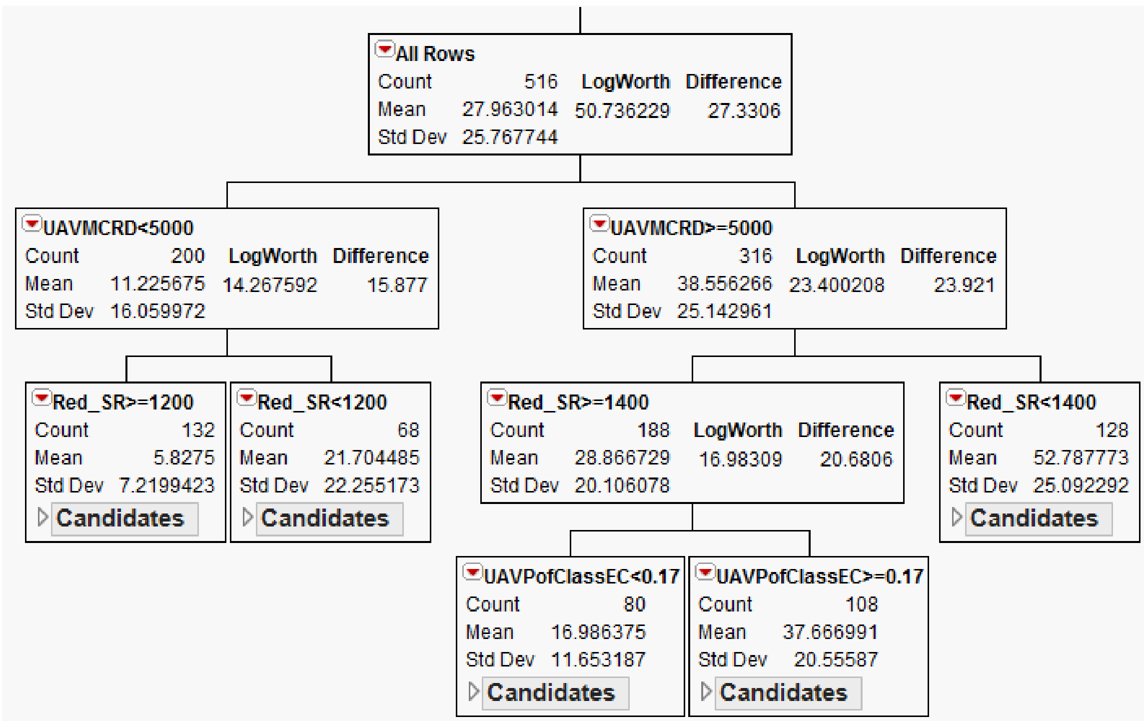


Figure 43. Partition tree model for the number of classified Red Agents.

Following the initial splits, we grow a regression tree with 20 splits and observe an R^2 value of 0.826 (The tree structure for first 13 splits is provided in Appendix E). Figure 44 displays the improvement of R^2 value with number of splits.

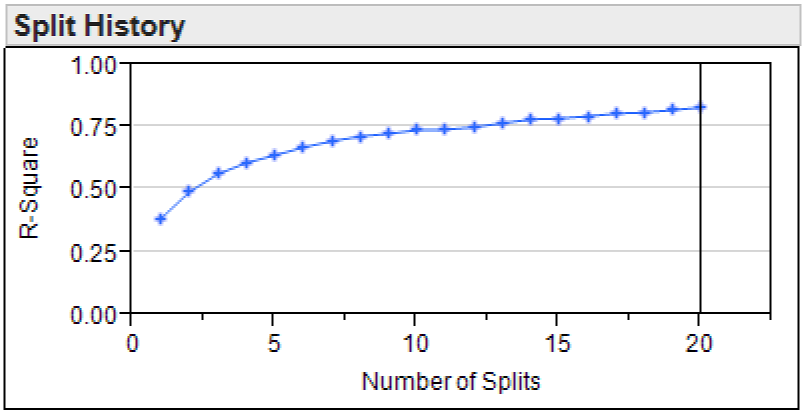


Figure 44. Split history of tree model.

The variable contributions to the explanatory power of the tree model are provided in Figure 45. The tree model indicates that we can explain variability in the response with a less complex model including just seven factors. Following the tree model, we fit a linear regression model with these highlighted seven factors and observe an R^2 value of 0.87. The results of the tree model yield that UAV classification performance is mainly driven by the classification range in the default state, but changes depending on the Red Team sensor range, UAV classification probability, number of UAVs, time between detections in default state, UAV speed, and UAV fuel level.

Column Contributions

Term	Number of Splits	SS
UAVMaxClassRange_Default	4	489.52044
Red_SensorRange	3	194.34537
UAVPClassAtMaxRange_EnContact	4	141.99616
NumberofUAVs	3	85.56303
UAVTimeBtwDetMax_Default	3	42.72079
UAVSpeed_Default	1	36.90650
UAVFuelLevel	1	10.52682

Figure 45. Variable contributions to the explanatory power of the tree model.

6. Random Forest Analysis

Random forests, first introduced by Leo Breiman, are “black-box” supervised learning methods for classification and regression. Thus, their interpretation capability is not as powerful as their prediction power. Random forests grow many classification trees, and these trees vote the most popular class for a given input set [48]. The number of trees and number of variables to try in each split can be determined by users. If we assume that a number of *m* variables can be used in each split, the algorithm randomly selects *m* variables out of all available candidates. Then, the best split is chosen over the *m* variables. Random forests grow the largest possible tree without pruning. We grow 500 trees and subset 4 variables to try in each split. The random forests model explains 94.36% of the variability in the response with a MSE of 0.1331.

Random forests can also be used to determine variable importance in a regression problem. The variable importance, based on a decrease in classification accuracy, pinpointed by the random forests model, can be seen in Figure 46. Similar to results of regression and tree analysis; random forests also highlight seven factors. We again see that UAV classification range in default state and Red Team sensor range have the highest impact on UAV performance in terms of detection and classification of Red Agents.

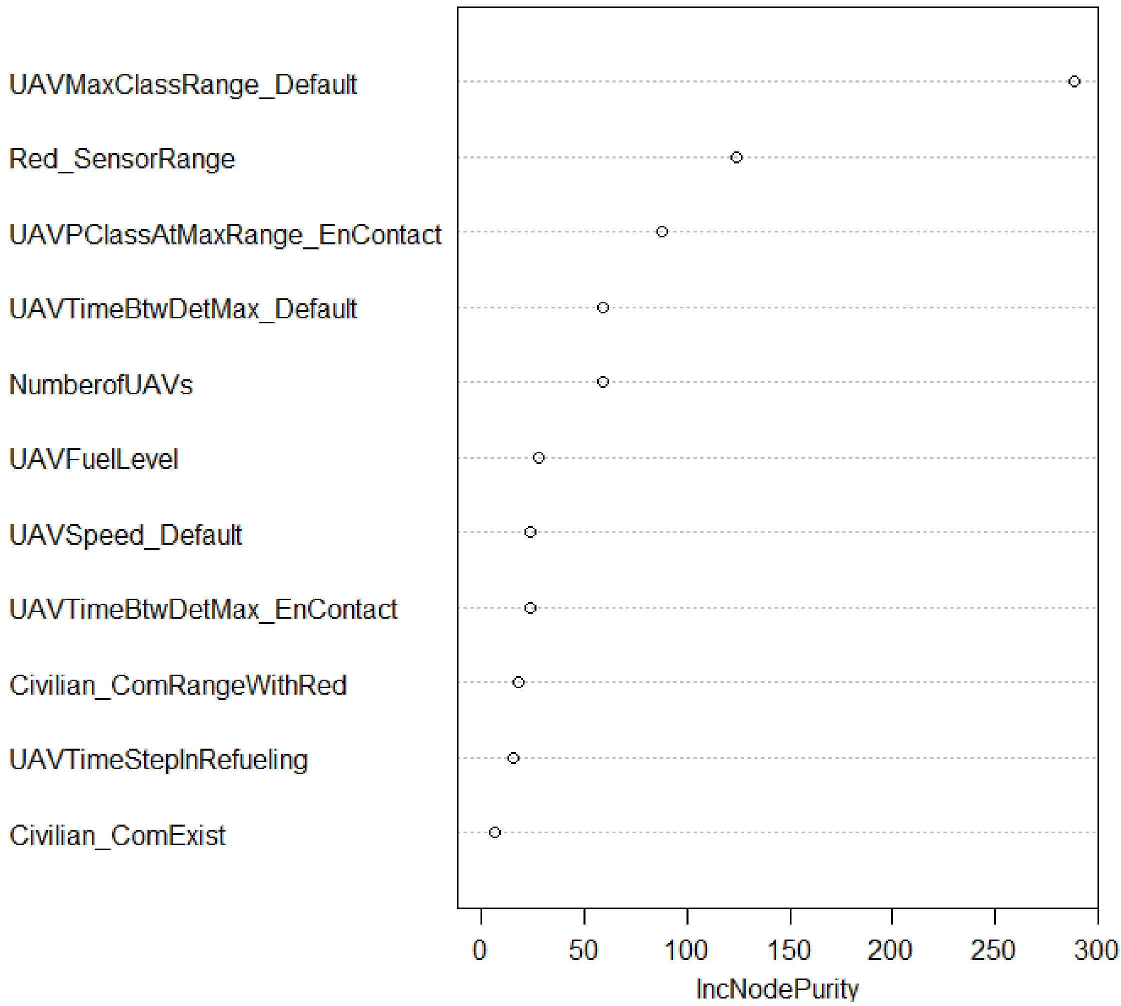


Figure 46. Sorted variable importance pinpointed by the random forests model.

THIS PAGE INTENTIONALLY LEFT BLANK

VI. CONCLUSION

The main purpose of this study is to explore the effectiveness of Unmanned Aerial Vehicles (UAVs) in helping secure a border characterized by rough terrain and active terrorists. Additionally, we investigated how the number of UAVs and performance characteristics contribute to border security.

We have identified some important factors related with UAVs and infiltration operations based on our scenarios. It would be almost impossible to model every aspect of an infiltration scenario. Yet, this was not the purpose of our study. We focus our study on gross level effects of factors of interest to look at if it is possible to use UAVs for intelligence, surveillance, and reconnaissance purposes over a hard topographical region.

We utilize four analysis techniques to study the mean number of classified Red Agents (terrorists): stepwise linear regression, lasso regression, regression trees, and random forests on the results of 103,200 simulated infiltration scenarios. The four analysis techniques highlight similar factors as the most important factors with additional insights.

A. PRIMARY FINDINGS

- Agent-based models provide us a modeling platform to create and analyze scenarios in a short time period.
- The data farming process is a powerful technique to study the effects of numerous factors simultaneously.
- The use of UAVs significantly enhances the detection and classification of terrorists operating or transiting in the region.
- The classification range of a UAV has a strong positive affect in the number of classified terrorists. First split of regression tree analysis highlights the importance of having a classification range greater than 5 km.
- The sensor range of terrorists to detect UAVs has a negative impact on the number of classified terrorists. Even though UAV altitude is not highlighted as a significant factor, assigning UAVs at higher altitudes can reduce their probability of detection by terrorists.

- The classification probability of a UAV is also important. A 1% increase in classification probability results in more classified terrorists. Additionally, regression tree analysis yields that a maximum range (≥ 5000 meters) classification probability greater than 0.17 provides better results in the classification of terrorists. From a practical sense, classification probability of a camera, which is onboard the UAV, leads to the number of effective looks needed to search an area. So, this is an important factor to take into account in terms of mission plan and organization.
- We cannot talk about an optimal number of UAVs to assign over the area of interest, but regression tree analysis indicates that assigning three or more UAVs results in more classified terrorists with a lower variance.
- The time between detections of entities is another important factor in terms of a UAV's classification capability. A one second increment of time between detections in the default state causes a larger decrease in the number of classified terrorists than a one second increment of time between detections in enemy contact state.
- Refueling time is a bigger determinant of success than the initial fuel level of a UAV. Thus, it is important for ground bases to be able to quickly get the UAVs back up.
- Increasing the UAV's speed in the default state has a negative impact on UAV classification performance. Regression tree analysis shows that UAV speeds higher than 250 km/hr noticeably decreases the number of classified terrorists. Therefore, the speed of flight is critical. If it is too high, UAVs will quickly occupy images of the terrain and will miss the details. On the contrary, if the speed is too low, then there will be less variation in the occupied image, hence less information will be gathered through the scans.
- The existence of communication links between the civilians and terrorists is another significant factor on UAV performance. The existence of civilian communication with terrorist caused a reduction in the number of classified terrorists. Therefore, SIGINT and electronic warfare capabilities can be considered in addition to UAV performance characteristics.

B. ADDITIONAL FINDINGS

- The stepwise linear regression indicates a significant interaction between classification range and classification probability. Increasing classification probability has a greater effect on the number of classified terrorists when the classification range is high.
- Another significant interaction highlighted by the stepwise linear regression is between terrorists' sensor range and civilian communication range with terrorists. For example, when the terrorist sensor range is low,

more advanced civilian communication abilities can still have a negative effect on the performance of a UAV.

- A third significant interaction emphasized by the stepwise linear regression is between the number of UAVs and UAV classification range. When the number of UAVs decreases, the number of classified terrorists is greater for increasing classification range. That is, higher performing UAVs can substitute for lower numbers.
- The lasso regression points out the interaction between the existence of civilian communication link and the range of this link. When the civilian communication link exists, the number of classified terrorists goes down with increasing range of the communication link.
- Finally, the lasso regression indicates the interaction between the civilian communication range with terrorists and time between detections of entities by UAVs. The civilian communication range has great effect on decreasing the number of classified terrorists when the time between detections is long.

C. FUTURE RESEARCH

This thesis provides many topics for follow-up studies. The following is a list of topics that could be examined:

- Use different paths for UAVs to follow over the area of interest.
- Use different refueling strategies, such as refueling on the ground or refueling in the air, to study the effects of refueling time on UAV classification performance in more detail. We did not assume a specific refueling strategy in our scenarios.
- Conduct a more focused scenario analysis including only the significant factors highlighted by this study.
- Examine the effects of different terrorist personalities. We assumed that terrorists have a perfect stealth value in enemy contact state and their propensity towards the destination degrades with the detection of UAVs.

THIS PAGE IS INTENTIONALLY LEFT BLANK

APPENDIX A. DEPENDENT VARIABLES THAT FORM THE DESIGN POINTS WITH FACTORS VARIED IN THE DESIGN

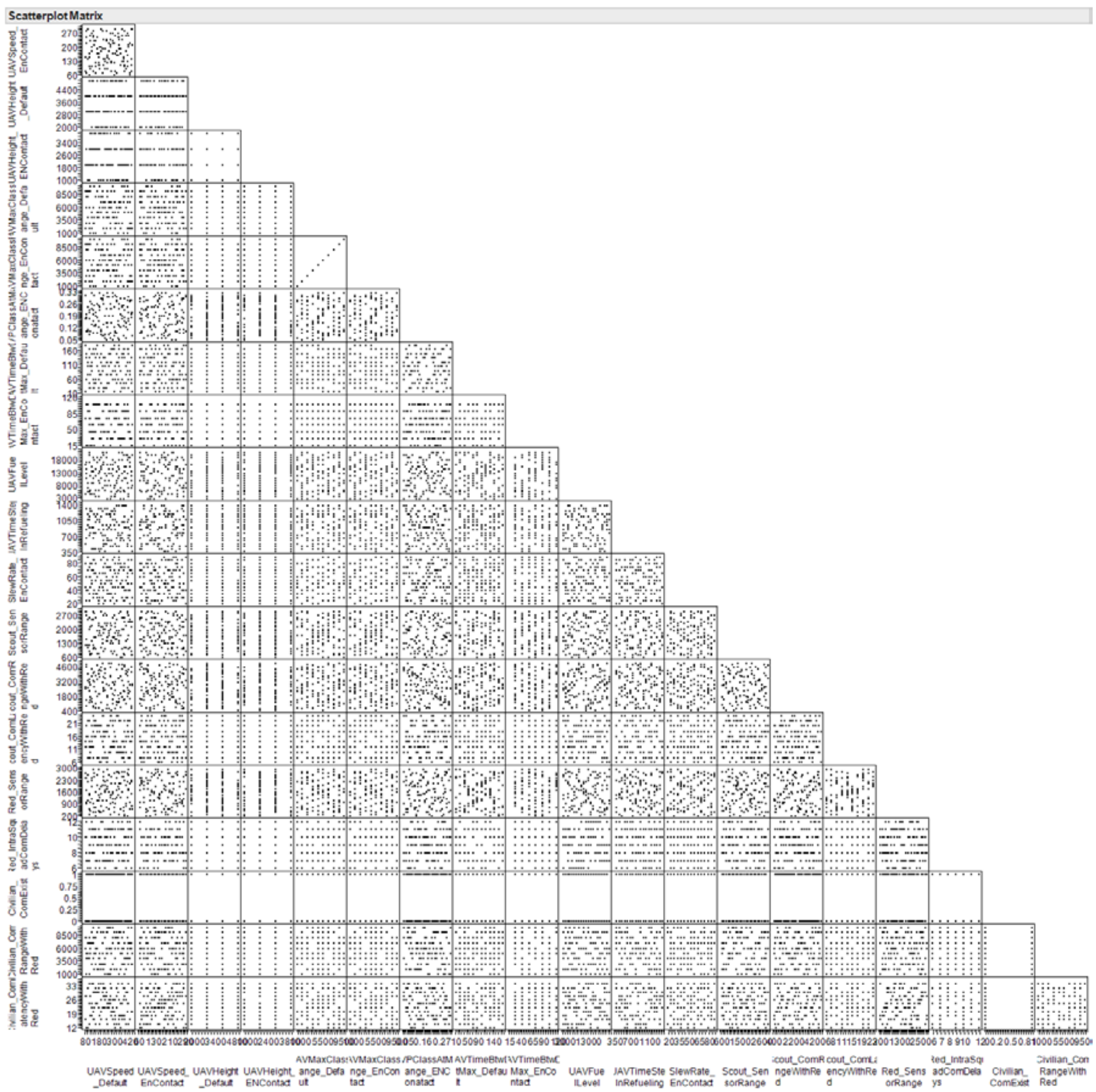
In addition to the factors varied in the design, there are also 13 dependent input variables that are set as a function of some factors: Unmanned Aerial Vehicle (UAV) classification range, UAV classification probability, time between detections, and UAV fuel usage rate. Here is the list of the dependent factors of our study:

	Factor Name	Unit	Type of Variable
UAV	Probability of Classification at Med. Range in Default State		continuous
	Probability of Classification at Min. Range in Default State		continuous
	Probability of Classification at Med. Range in Enemy Contact State		continuous
	Probability of Classification at Min. Range in Enemy Contact State		continuous
	Classification Range in Default State (Med.)	m	continuous
	Classification Range in Default State (Min.)	m	continuous
	Classification Range in Enemy Contact State (Med.)	m	continuous
	Classification Range in Enemy Contact State (Min.)	m	continuous
	Time Between Detection at Default State (Med.)	seconds	continuous
	Time Between Detection at Default State (Min.)	seconds	continuous
	Time Between Detection at Enemy Contact State (Med.)	seconds	continuous
	Time Between Detection at Enemy Contact State (Min.)	seconds	continuous
	Fuel Usage Rate in Refueling State	unit	continuous

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX B. SCATTERPLOT MATRIX FOR ALL FACTORS

The scatterplot matrix for all factors, including controllable and uncontrollable factor shows the space filling property of our Nearly Orthogonal Latin Hypercube Design (NOLH).



THIS PAGE INTENTIONALLY LEFT BLANK

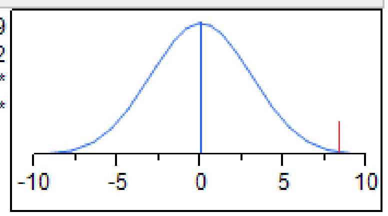
APPENDIX C. DETAILED COMPARISONS REPORT FOR T-TEST

The following provides the paired t-test comparisons for the number of classified Red Agents with different number of UAVs, with each assigned its own Area of Responsibility (AOR).

Detailed Comparisons Report

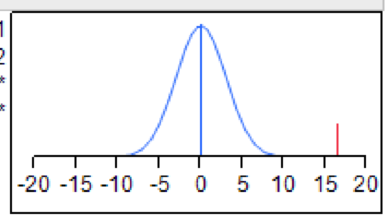
Comparing 2AOR with 1AOR

Difference	8.2998	t Ratio	2.739749
Std Err Dif	3.0294	DF	512
Upper CL Dif	14.2514	Prob > |t|	0.0064*
Lower CL Dif	2.3482	Prob > t	0.0032*
Confidence	0.95	Prob < t	0.9968



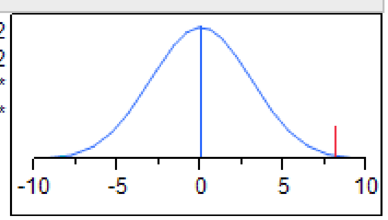
Comparing 3AOR with 1AOR

Difference	16.4651	t Ratio	5.4351
Std Err Dif	3.0294	DF	512
Upper CL Dif	22.4167	Prob > |t|	<.0001*
Lower CL Dif	10.5135	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



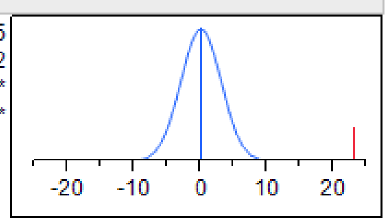
Comparing 3AOR with 2AOR

Difference	8.1653	t Ratio	2.695352
Std Err Dif	3.0294	DF	512
Upper CL Dif	14.1169	Prob > |t|	0.0073*
Lower CL Dif	2.2137	Prob > t	0.0036*
Confidence	0.95	Prob < t	0.9964



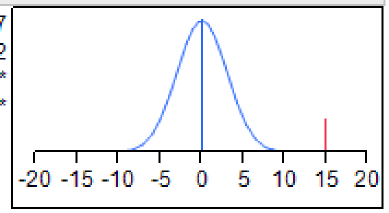
Comparing 4AOR with 1AOR

Difference	23.1242	t Ratio	7.633245
Std Err Dif	3.0294	DF	512
Upper CL Dif	29.0758	Prob > |t|	<.0001*
Lower CL Dif	17.1726	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



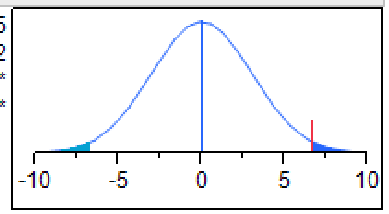
Comparing 4AOR with 2AOR

Difference	14.8244	t Ratio	4.893497
Std Err Dif	3.0294	DF	512
Upper CL Dif	20.7760	Prob > |t|	<.0001*
Lower CL Dif	8.8728	Prob > t	<.0001*
Confidence	0.95	Prob < t	1.0000



Comparing 4AOR with 3AOR

Difference	6.6591	t Ratio	2.198145
Std Err Dif	3.0294	DF	512
Upper CL Dif	12.6107	Prob > |t|	0.0284*
Lower CL Dif	0.7075	Prob > t	0.0142*
Confidence	0.95	Prob < t	0.9858

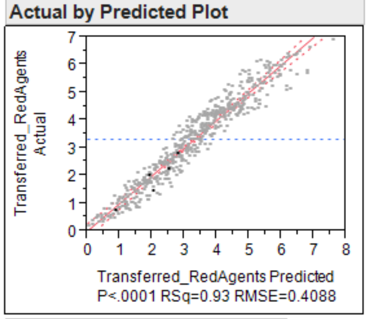


APPENDIX D. STATISTICAL RESULTS OF THE MODEL WITH INTERACTIONS

We fit a saturated model first including all pairwise interactions among the significant factors. Here are the statistical results and sorted parameter estimates for the model exploring all two-way interactions:

Response Transferred_RedAgents

Actual by Predicted Plot



Summary of Fit

RSquare	0.93342
RSquare Adj	0.929302
Root Mean Square Error	0.408777
Mean of Response	3.315134
Observations (or Sum Wgts)	516

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	30	1136.1869	37.8729	226.6505
Error	485	81.0426	0.1671	Prob > F
C. Total	515	1217.2295		<.0001*

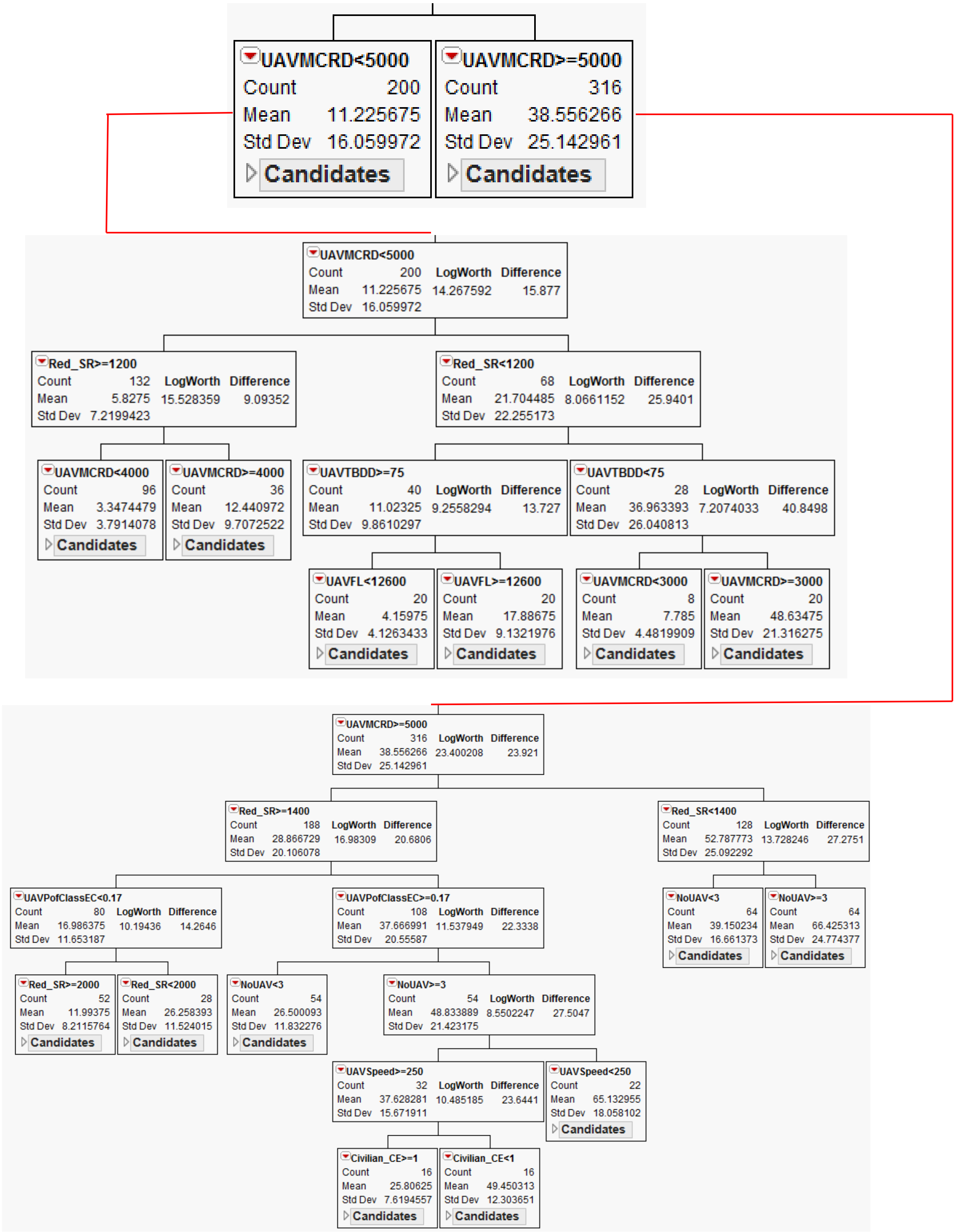
Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
UAVMaxClassRange_Default	0.0003716	6.801e-6	54.64	<.0001*
Red_SensorRange	-0.000776	0.000022	-35.14	<.0001*
UAVPClassAtMaxRange_EnContact	5.7639458	0.220964	26.09	<.0001*
NumberofUAVs	0.4190199	0.016096	26.03	<.0001*
UAVTimeBtwDetMax_Default	-0.007961	0.000373	-21.34	<.0001*
UAVFuelLevel	2.853e-5	3.259e-6	8.75	<.0001*
UAVTimeBtwDetMax_EnContact	-0.004241	0.000577	-7.35	<.0001*
(UAVSpeed_Default-270.155)*(Civilian_ComRangeWithRed-5503.88)	5.4167e-7	7.813e-8	6.93	<.0001*
(Red_SensorRange-1601.55)*(Civilian_ComRangeWithRed-5503.88)	8.114e-8	1.175e-8	6.91	<.0001*
(UAVMaxClassRange_Default-5503.88)*(Civilian_ComExist-0.50388)	8.6867e-5	0.000014	6.17	<.0001*
UAVTimeStepInRefueling	-0.000333	5.74e-5	-5.80	<.0001*
(UAVPClassAtMaxRange_EnContact-0.19016)*(UAVTimeBtwDetMax_Default-97.5581)	-0.035473	0.006614	-5.36	<.0001*
(UAVTimeStepInRefueling-900.465)*(Civilian_ComExist-0.50388)	-0.000669	0.000126	-5.33	<.0001*
Civilian_ComExist	-0.193103	0.036357	-5.31	<.0001*
(NumberofUAVs-2.5)*(UAVMaxClassRange_Default-5503.88)	0.0000319	6.057e-6	5.27	<.0001*
(UAVPClassAtMaxRange_EnContact-0.19016)*(Civilian_ComExist-0.50388)	-2.161187	0.454446	-4.76	<.0001*
(UAVSpeed_Default-270.155)*(UAVTimeBtwDetMax_EnContact-67.5581)	-0.000025	5.3e-6	-4.70	<.0001*
(UAVMaxClassRange_Default-5503.88)*(Red_SensorRange-1601.55)	3.9013e-8	8.565e-9	4.55	<.0001*
UAVSpeed_Default	-0.000755	0.000172	-4.39	<.0001*
(UAVFuelLevel-12153.5)*(UAVTimeStepInRefueling-900.465)	5.3982e-8	1.254e-8	4.30	<.0001*
(UAVSpeed_Default-270.155)*(UAVTimeStepInRefueling-900.465)	2.4764e-6	5.858e-7	4.23	<.0001*
(UAVTimeBtwDetMax_Default-97.5581)*(UAVTimeStepInRefueling-900.465)	4.7689e-6	1.183e-6	4.03	<.0001*
Civilian_ComRangeWithRed	-2.525e-5	6.779e-6	-3.72	0.0002*
(UAVMaxClassRange_Default-5503.88)*(UAVTimeBtwDetMax_Default-97.5581)	-5.431e-7	1.532e-7	-3.54	0.0004*
(UAVMaxClassRange_Default-5503.88)*(UAVFuelLevel-12153.5)	-4.297e-9	1.399e-9	-3.07	0.0022*
(UAVMaxClassRange_Default-5503.88)*(Civilian_ComRangeWithRed-5503.88)	-8.966e-9	3.275e-9	-2.74	0.0064*
(NumberofUAVs-2.5)*(Red_SensorRange-1601.55)	-5.325e-5	1.974e-5	-2.70	0.0072*
(NumberofUAVs-2.5)*(UAVTimeBtwDetMax_Default-97.5581)	-0.000857	0.000333	-2.57	0.0104*
(UAVFuelLevel-12153.5)*(Civilian_ComExist-0.50388)	1.5637e-5	0.000007	2.23	0.0260*
(NumberofUAVs-2.5)*(UAVPClassAtMaxRange_EnContact-0.19016)	0.4014043	0.19737	2.03	0.0425*

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX E. TREE STRUCTURE FOR FIRST 13 SPLITS

Regression trees recursively partition data to find an optimal split on the response. After each split, the succeeding ideal split is determined within each partition. We grow a regression tree with 20 splits. The tree structure for first 13 splits is provided below.


UAVMCRD<5000 Count 200 Mean 11.225675 Std Dev 16.059972 Candidates
UAVMCRD>=5000 Count 316 Mean 38.556266 Std Dev 25.142961 Candidates
UAVMCRD<5000 Count 200 Mean 11.225675 Std Dev 16.059972 LogWorth 14.267592 Difference 15.877
Red_SR>=1200 Count 132 Mean 5.8275 Std Dev 7.2199423 LogWorth 15.528359 Difference 9.09352
Red_SR<1200 Count 68 Mean 21.704485 Std Dev 22.255173 LogWorth 8.0661152 Difference 25.9401
UAVMCRD<4000 Count 96 Mean 3.3474479 Std Dev 3.7914078 Candidates
UAVMCRD>=4000 Count 36 Mean 12.440972 Std Dev 9.7072522 Candidates
UAVTBDD>=75 Count 40 Mean 11.02325 Std Dev 9.8610297 LogWorth 9.2558294 Difference 13.727
UAVTBDD<75 Count 28 Mean 36.963393 Std Dev 26.040813 LogWorth 7.2074033 Difference 40.8498
UAVFL<12600 Count 20 Mean 4.15975 Std Dev 4.1263433 Candidates
UAVFL>=12600 Count 20 Mean 17.88675 Std Dev 9.1321976 Candidates
UAVMCRD<3000 Count 8 Mean 7.785 Std Dev 4.4819909 Candidates
UAVMCRD>=3000 Count 20 Mean 48.63475 Std Dev 21.316275 Candidates
UAVMCRD>=5000 Count 316 Mean 38.556266 Std Dev 25.142961 LogWorth 23.400208 Difference 23.921
Red_SR>=1400 Count 188 Mean 28.866729 Std Dev 20.106078 LogWorth 16.98309 Difference 20.6806
Red_SR<1400 Count 128 Mean 52.787773 Std Dev 25.092292 LogWorth 13.728246 Difference 27.2751
UAVPofClassEC<0.17 Count 80 Mean 16.986375 Std Dev 11.653187 LogWorth 10.19436 Difference 14.2646
UAVPofClassEC>=0.17 Count 108 Mean 37.666991 Std Dev 20.55587 LogWorth 11.537949 Difference 22.3338
NoUAV<3 Count 64 Mean 39.150234 Std Dev 16.661373 Candidates
NoUAV>=3 Count 64 Mean 66.425313 Std Dev 24.774377 Candidates
Red_SR>=2000 Count 52 Mean 11.99375 Std Dev 8.2115764 Candidates
Red_SR<2000 Count 28 Mean 26.258393 Std Dev 11.524015 Candidates
NoUAV<3 Count 54 Mean 26.500093 Std Dev 11.832276 Candidates
NoUAV>=3 Count 54 Mean 48.833889 Std Dev 21.423175 LogWorth 8.5502247 Difference 27.5047
UAVSpeed>=250 Count 32 Mean 37.628281 Std Dev 15.671911 LogWorth 10.485185 Difference 23.6441
UAVSpeed<250 Count 22 Mean 65.132955 Std Dev 18.058102 Candidates
Civilian_CE>=1 Count 16 Mean 25.80625 Std Dev 7.6194557 Candidates
Civilian_CE<1 Count 16 Mean 49.450313 Std Dev 12.303651 Candidates

LIST OF REFERENCES

[1] “Turkey, a partner in the war on terror: Middle East Forum” [Online]. Available: http://www.meforum.org/299/turkey-a-partner-in-the-war-on-terror.

[2] “Turkey – location and size, territories and dependencies, Climate, Topographic regions, Oceans and seas” [Online]. Available: http://www.nationsencyclopedia.com/geography/Slovenia-to-Zimbabwe-Cumulative-Index/Turkey.html.

[3] “Turkey’s border porosity problem with PKK | Small Wars Journal” [Online]. Available: http://smallwarsjournal.com/jrnl/art/turkeys-border-porosity-problem-with-pkk.

[4] B. of P. A. U.S. Department Of State, Office of website Management. (2012, Sept. 28). *Foreign Terrorist Organizations* [Online]. Available: http://www.state.gov/j/ct/rls/other/des/123085.htm.

[5] “TURKEY - PKK steps up attacks in Turkey” [Online]. Available: http://www.hurriyetdailynews.com/default.aspx?pageid=438&n=pkk-steps-up-attacks-in-turkey-2010–05–30.

[6] “Turk soldier, PKKs die in SE clashes” [Online]. Available: http://edition.presstv.ir/detail/128756.html.

[7] “Five killed in Istanbul blast” [Online]. Available: http://edition.presstv.ir/detail/131456.html.

[8] “Kurdish militants kill 10 in attacks on Turkish forces” [Online]. Available: http://www.trust.org/alertnet/news/kurdish-militants-kill-10-in-attacks-on-turkish-forces/.

[9] “Kurdish militants kill 10 Turkish troops in convoy raid” [Online]. Available: http://www.trust.org/alertnet/news/kurdish-militants-kill-10-turkish-troops-in-convoy-raid/.

[10] “PKK bomb kills Turkish police” [Online]. Available: http://www.bbc.co.uk/news/world-europe-19615995.

[11] “Powerful blast rocks eastern Turkish city, seven reportedly killed (PHOTOS)” [Online]. Available: http://rt.com/news/powerful-rocks-eastern-city-959/.

[12] “Kurdish militants kill 10 Turkish troops in convoy raid” [Online]. Available: http://www.trust.org/alertnet/news/kurdish-militants-kill-10-turkish-troops-in-convoy-raid/.

[13] J. Butler, “UAVs and ISR Sensor Technology,” Air Command and Staff Collage Air University Maxwell AFB, Alabama, 033, Apr. 2001.

[14] A. V. Burman, “Getting the Biggest Bang for the Buck,” *Government Executive*, vol. 33, no. 1, p. 66, Jan. 2001.

[15] “USAF may expand A-10 MOD effort at same cost -- and get it sooner” [Online]. Available: http://insidedefense.com.libproxy.nps.edu/Inside-the-Pentagon/Inside-the-Pentagon-11/09/2000/usaf-may-expand-a-10-mod-effort-at-same-cost-and-get-it-sooner/menu-id-148.html.

[16] “U.S. Unmanned Aerial Systems - Report to Congress 2012” [Online]. Available: http://www.scribd.com/doc/100106417/U-S-Unmanned-Aerial-Systems-Report-to-Congress-2012.

[17] S. Hamilton. (2011, Feb.). *Here’s a thought: The Pentagon wants ‘thinking’ drones [Online].* Available: http://www.nationaldefensemagazine.org /archive/2011/February/Pages/Here%E2%80%99saThoughtThePentagon Wants%E2%80%98Thinking%E2%80%99Drones.aspx.

[18] “U.S. Customs and Border Protection - Border Security” [Online]. Available: http://www.cbp.gov/xp/cgov/border_security/am/.

[19] “Congressional Research Service Reports - General National Security” [Online]. Available: http://www.fas.org/sgp/crs/natsec/index.html.

[20] K. Oh, “Exploration of Border Security Systems of the ROK Army Using Agent-Based Modeling and Simulation,” M.S. thesis, Dept. of Engineering, University of Texas at Austin, 2010.

[21] B. Oliver, “Could UAVs improve New Zealand’s maritime security?” M. Phil. thesis, Massey Univ. Centre for Defense Studies, 2009.

[22] B. Yildiz, “Exploration of the use of unmanned aerial vehicles along with other assets to enhance border protection,” M.S. thesis, Dept. of Oper. Res., Naval Postgraduate School, Monterey, CA, 2009.

[23] C. A. Sulewski, “An exploration of unmanned aerial vehicles in the Army’s future combat systems family of systems,” M.S. thesis, Dept. of Oper. Res., Naval Postgraduate School, Monterey, CA, 2005.

[24] M. Raffetto, “Unmanned aerial vehicle contributions to intelligence, surveillance, and reconnaissance operations,” M.S. thesis, Dept. of Oper. Res., Naval Postgraduate School, Monterey, CA, 2004.

[25] K. Bertsche and G. Schwarz, “Agent Based Simulation of Terrorist Attacks ‘Protecting of Potential Targets’.” The Cornwallis Group IX: Analysis for Stabilization and Counter Terrorist Operations, 2002 [Online]. Available: http://www.thecornwallisgroup.org/pdf/2004_26BertscheCIX-12Oct.pdf

[26] S. M. Sanchez and T. W. Lucas, “Exploring the world of agent-based simulations: simple models, complex analyses: exploring the world of agent-based simulations: simple models, complex analyses,” *Proc. of the 34th Conference on Winter Simulation: Exploring New Frontiers*, pp. 116–126, 2002.

[27] E. Bonabeau, “Agent-based modeling: methods and techniques for simulating human systems,” *Proc. of the Nat. Acad. of Sci.*, vol. 99, no. 90003, pp. 7280–7287, May 2002.

[28] WorldCat.org. (2007). *MANA (Map Aware Non-uniform Automata) version 4.0 User Manual [Online].* Available: http://www.worldcat.org/title/mana-map-aware-non-uniform-automata-version-40-user-manual/oclc/174097443&referer=brief_results.

[29] SEED Center for Data Farming [Online]. Available: http://harvest.nps.edu/.

[30] E. S. Wolf, “Using agent-based distillations to explore logistics support to urban, humanitarian assistance/disaster relief operations,” M.S. thesis, Dept. of Oper. Res., Naval Postgraduate School, Monterey, CA, 2003.

[31] V. Pfeiffer, “Communication aspects in urban terrain,” M.S. thesis, Dept. of Oper. Res., Naval Postgraduate School, Monterey, CA, 2006.

[32] F. Martinez Tiburcio, “Maritime protection of critical infrastructure assets in the Campeche Sound,” M.S. thesis, Dept. of Oper. Res., Naval Postgraduate School, Monterey, CA, 2005.

[33] R. K. Cason, “Analysis of the Vertical Takeoff and landing Unmanned Aerial Vehicle (VTUAV) in small unti urban operations,” M.S. thesis, Dept. of Oper. Res., Naval Postgraduate School, Monterey, CA, 2004.

[34] Mehmet Aydin, “An exploratory analysis of village search operations,” M.S. thesis, Dept. of Oper. Res., Naval Postgraduate School, Monterey, CA, 2004 [Online]. Available: http://calhoun.nps.edu /public/handle/10945/1611.

[35] D. Singham, M. Therkildsen, and L. Schruben, “Applications of Flocking Algorithms to Input Modeling for Agent Movement,” *Proc. of the 2000 Winter Simulation Conference*, Phoenix, AZ, pp. 2443–2449, Dec. 2011.

[36] T. Genichi and W. Yuin, *Introduction to Off-Line Quality Control*. Central Japan Quality Association, 1985.

[37] S. M. Sanchez, “A robust design tutorial,” *Proc. of the 26th Conference on Winter Simulation*, San Diego, CA, pp. 106–113, Dec. 1994.

[38] S. M. Sanchez, “Robust Design: Seeking the Best of All Possible Worlds,” *Proc. of the 2000 Winter Simulation Conference,* Orlando, FL, vol. 1, pp. 69–76, Dec. 2000.

[39] T. M. Cioppa and T. W. Lucas, “Efficient Nearly Orthogonal and Space-filling Latin Hypercubes,” *Technometrics*, vol. 49, no. 1, pp. 45–55, Feb. 2007.

[40] S. Sanchez and H. Wan, “Better than a Petaflop: The Power of Efficient Experimental Design,” *IEEE*, pp. 60–74, Dec. 2009.

[41] “Statistics Software - Data Analysis - DOE - Six Sigma - JMP Software” [Online]. Available: http://www.jmp.com/.

[42] “The R Project for Statistical Computing” [Online]. Available: http://www.r-project.org/.

[43] J. J. Faraway, *Extending the Linear Model with R (Generalized Linear, Mixed Effects and Nonparametric Regression Models)*. Taylor & Francis Group, LLC, 2006.

[44] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning.* New York: Springer, 2001.

[45] R. Tibshirani, *Journal of the Royal Statistical Society*, vol. 58, 1996.

[46] “4.6 - The Lasso | STAT 897D - Applied Data Mining” [Online]. Available: https://onlinecourses.science.psu.edu/stat857/node/158.

[47] W.-Y. Loh, “Classification and Regression Trees,” vol. 1, p. 14, Feb. 2011.

[48] L. Breiman, “Random Forests,” *Kluwer Academic Publishers, Manufactured in the Netherlands*, pp. 5–32, Apr. 2001.

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California